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The Causes and Consequences of Managerial Discrimination Among Analysts During Earnings Conference Calls

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The Causes and Consequences of Managerial Discrimination Among Analysts During Earnings Conference Calls

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Dedication

To Rebecca and Will

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The Causes and Consequences of Managerial Discrimination Among Analysts During Earnings Conference Calls

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This dissertation investigates two fundamental issues regarding managerial discrimination among analysts during earnings conference calls. Discrimination is defined as a manager systematically choosing to interact more (less) with analysts holding favorable (unfavorable) views of the firm during earnings conference calls. The first issue is whether discrimination exists. The second issue is whether discrimination impacts the market's interpretation of quarterly earnings news. Examining these issues is important because lawmakers and the SEC are concerned that discrimination exists and may have detrimental effects on investors.

To provide empirical evidence on the existence of discrimination, I examine the association between individual analyst participation on a firm's quarterly earnings conference call and the outstanding stock recommendation of the analyst. I find that the probability of an analyst being allowed to participate (i.e., to ask a question) during a conference call is increasing in the analyst's view of the firm. Additionally, such differential analyst treatment is more (less) pronounced when managers have higher

(lower) incentives to maintain high stock prices, and when analysts are more (less) reliant on management for information.

To assess the impact of discrimination on the market's assessment of earnings news, I first classify sample conference calls as discriminating and non-discriminating. I then examine the market reaction to earnings news in settings where the manager holds discriminating and non-discriminating conference calls. I find that the market reaction to large magnitude good news earnings surprises is amplified when the manager discriminates. On the contrary, the market reaction to small magnitude good news earnings and both large and small bad earnings news is invariant to the discrimination level of conference call. Further investigation of the incremental market reaction to large magnitude good news earnings for discriminating managers reveals that such reaction persists in the presence of relative sophisticated and unsophisticated investors. Additionally, good news firms that discriminate exhibit less post earnings announcement drift than non-discriminating firms. These results are more consistent with discrimination assisting the market in digesting the implications of good earnings news as opposed to aiding the manager in overselling those implications.

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Chapter 1: Introduction

This dissertation investigates two fundamental issues regarding managerial discrimination among analysts during earnings conference calls. I define discrimination as a manager systematically choosing to interact during the conference call more (less) with analysts holding favorable (unfavorable) views of the firm. The first issue is whether discrimination exists. The second is whether discrimination impacts the market's interpretation of quarterly earnings news.

In Chapter 2, I investigate whether managers discriminate among analysts during earnings conference calls based on how favorably the analyst views the firm. Lawmakers and the SEC are currently considering a push for legal reform to eliminate this type of discrimination despite the absence of systematic empirical evidence regarding the existence or extent of such discrimination. Using a large sample of earnings conference call transcripts, representing 19,677 firm-quarters and 146,708 analyst-firm-quarter observations between 2002 and 2004, I find that the probability of an analyst being allowed to participate (i.e., to ask a question) during a conference call is increasing in the analyst's view of the firm. In particular, the odds of an analyst with a strong buy recommendation participating on a conference call are more than double those of an analyst with a strong sell recommendation.

Such differential analyst treatment is more (less) pronounced when managers have higher (lower) incentives to maintain high stock prices, and when analysts are more (less) reliant on management for information. Additionally, discrimination appears to exist even among those analysts allowed to ask questions during the conference call. Conditional on participating, the order of analyst appearance on the conference call is an increasing function of the analyst's view of the firm. Combined these findings validate prior anecdotal and survey evidence suggesting that managers discriminate among analysts and documents that such discrimination is statistically and economically significant.

In Chapter 3, I investigate the association between the market reaction to quarterly earnings news and managerial conference call discrimination among analysts. I consider the possibility that the "scrutiny" of the questions analysts pose to managers during earnings conference calls decreases in the favorableness of the analyst's view of the firm. Under such a scenario, managerial discrimination – the act of granting (thwarting) conference call participation to favorable (unfavorable) analysts – is more likely to result in conference calls that highlight (suppress) positive (negative) aspects of the firm, possibly making good (bad) earnings news look better than (not as bad as) it really is. Understanding how investors view earnings news in the presence of discrimination is important because regulators and the SEC have recently voiced concerns that discrimination during earnings conference calls may potentially mislead investors (Cox 2005).

For a random sample of earnings conference call manager-analyst dialogs, I begin by showing that question scrutiny is decreasing in the favorableness of the analyst's view of the firm. That is, more favorable analysts ask less scrutinizing questions. However, this effect only exists for firms that meet or beat expected earnings. For firms that miss quarterly earnings targets, both favorable and unfavorable analysts become equally scrutinizing on average.

I then classify conference calls as "discriminating" and "non-discriminating" to assess how the market views earnings news in each setting. Managers hosting discriminating (non-discriminating) conference calls interact with analysts that hold views more favorable (unfavorable) than the consensus view of the firm held by the population of analysts following the firm. I find that the market reaction to large magnitude good news earnings surprises is amplified when the manager discriminates, which is potentially consistent with regulatory concerns. I find no evidence of discriminatory effects for small magnitude earnings surprises. Additionally, the market reaction to bad earnings news, both large and small, is invariant to the type of conference call held, consistent with the lack of a relation between question scrutiny and the favorableness of the analyst's view of the firm when a firm misses earnings targets.

The regulatory perspective on discrimination interprets the positive incremental market reaction to good news earnings as unsophisticated investors being fooled into over-reacting to good news earnings. Further investigation of the regulatory perspective reveals that the effect of discrimination on the market reaction to earnings news exists to an equal extent among both sophisticated and unsophisticated investors. Additionally, good news firms that discriminate exhibit less post earnings announcement drift than non-discriminating firms. This implies that discrimination assists the market in digesting the implications of large magnitude good news earnings as opposed to aiding the manager in overselling those implications.

Combined, the effects of discrimination on the market reaction to earnings news are inconsistent with regulatory concerns and more consistent with managers taking advantage of the less scrutinizing environment discrimination brings to more fully elaborate on the firm's prospects and resolve uncertainty in the marketplace.

Chapter 2: Evidence of Management Discrimination Among Analysts During Earnings Conference Calls

2.1 Introduction

This chapter investigates whether managers discriminate among analysts by allowing conference call participation based on how favorably the analyst views the firm. Under Regulation FD, managers cannot privately disseminate material information to particular analysts. However, managers retain the flexibility to publicly provide information to analysts of their choosing. Concerned that managers use this flexibility to pressure analysts into positively biased research by accepting (thwarting) conference-call questions from favorable (unfavorable) analysts, the SEC is considering a push for legal reform (Cox 2005). However, the SEC's concerns are based primarily on anecdotal and survey evidence of managerial discrimination. Anecdotes may not indicate a systematic problem and analyst survey results may be biased because analysts have incentives to push for laws that reduce information search costs. This chapter seeks to provide direct empirical evidence on whether, and to what extent, discrimination exists during conference calls.

I use a new and extensive dataset of conference call transcripts between 2002 and 2004 to directly measure various aspects of analyst participation during conference calls. Transcripts indicate which analysts asked questions during the conference call, when they asked the questions relative to other conference call participants, and how long managers interacted with each analyst. I use I/B/E/S to identify a population of analysts who would likely seek conference call participation and to measure analyst characteristics, including the analyst's view of the firm. Using data from these two sources, I model analyst conference call participation as a function of the favorableness of the analyst's view of the firm while controlling for other factors associated with analyst participation.

I find that the probability of an analyst asking a question during a firm's earnings conference call increases with the favorableness of the analyst's stock recommendation for the firm. After controlling for other factors, the odds of analysts with strong buy recommendations for a firm (i.e., favorable analysts) asking a conference call question are more than double those of analysts with strong sell recommendations (i.e., unfavorable analysts). This provides strong evidence to support claims that firms discriminate by rewarding (punishing) analysts with favorable (unfavorable) views of the firm. The differential treatment of favorable analysts relative to unfavorable analysts is higher when managers' incentives to maintain high stock prices are higher and when analysts must rely heavily on management-provided information. Additionally, discrimination exists even among analysts who participate on the call. Favorable analysts are allowed to ask their questions before unfavorable analysts, consistent with managers manipulating the question queue in a discriminatory fashion.

This chapter adds to the empirical literature in a number of ways. First, I directly measure a specific type of management discrimination. Recent studies (Ke and Yu 2005, Huang et al. 2005, Chen and Matsumoto 2005) have used analyst earnings forecast accuracy as an indirect proxy for management discrimination because management discrimination is generally unobservable. By design, studies using indirect proxies cannot distinguish between the absence of discrimination and failed discrimination attempts, nor can they provide insight as to the discrimination method managers used.

Second, I add to a management discrimination literature that has reached mixed conclusions. Using analyst earnings forecast accuracy to proxy for differential managerial access, Ke and Yu (2005) provide evidence that managers provide better information access to favorable analysts compared to unfavorable analysts. They interpret their evidence as consistent with discrimination. In contrast, Huang et al. (2005) find that unfavorable (favorable) analysts actually issue more (less) accurate future earnings forecasts, inconsistent with managerial discrimination. I provide direct evidence consistent with Ke and Yu's (2005) conclusion regarding the existence of discrimination.

Third, I focus exclusively on the post Regulation FD period, which increases the applicability of my findings to current debates on management discrimination. Extant research tests the discrimination hypothesis prior to the passage of Regulation FD. Because Regulation FD removed private communications of material information from management's discrimination toolkit, the generalizability of extant results to current regulatory regimes is unclear. One exception is Chen and Matsumoto (2005), who conclude that managers discriminated before, but not after, the passage of Regulation FD. Their lack of evidence post Regulation FD is inconsistent with growing anecdotal claims that discrimination still exists (Mayo 2006, Lowengard 2006, Morgenson 2005, SIA 2005, Cox 2005, Davis 2004, Kelly 2003, Solomon and Frank 2003).

This chapter proceeds as follows. Section 2 reviews the literature and develops the discrimination hypotheses. Section 3 outlines the sample selection, variable measurement and research design for testing whether managers differentially allow conference call participation based on the favorableness of the analyst's view of the firm. Section 4 presents the empirical results regarding differential conference call participation, and

Section 5 assesses whether the results vary with managerial incentives and analyst reliance on management-provided information. Section 6 investigates discrimination among those analysts who do participate on the conference call, and Section 7 concludes.

2.2 Literature Review and Hypothesis Development

Underpinnings of Managerial Discrimination. The discrimination hypothesis posits that more (less) managerial access will be provided to analysts when their views of the firm are favorable (unfavorable). Discrimination results from both a manager's desire for high stock prices and an analyst's need for manager-provided firm-specific information. By allowing differential analyst access, managers make it more costly for unfavorable analysts to gather information and compete with more favorable analysts. Unfavorable analysts are then forced to either drop coverage or improve their view of the firm in order to obtain the information necessary to effectively provide information intermediary services. In this way, managers attempt to drown out negative information about the firm which should result in more favorable analyst views of the firm persisting in the market.

If discrimination successfully biases analyst research in the manager's favor and forces unfavorable analysts from the market, investors relying on available sell-side analyst research could be misled. The SEC, in the interest of protecting investors from biased information, has recently voiced concerns that manager discrimination during conference calls is a serious problem that may require legislative action (Cox 2005). The SEC's particular concern with the pressures managers impart on analysts is part of a broader crackdown on pressures analysts face to issue positively biased research. The Global

Settlement and Regulation Analyst Certification, both in 2003, were intended to remove pressures analysts faced from the investment banking side of the brokerage house.

Anecdotal evidence outlines how managers in particular might discriminate, including not inviting unfavorable analysts to meetings where material information will be communicated (Siconolfi 1995), not returning their phone calls (Angwin and Peers 2001), and not allowing them to ask questions during conference calls (Kelly 2003). Regulation FD, passed in 2000, was meant to curb the differential treatment of analysts by preventing managers from privately disclosing material information to certain analysts and not others. Despite Regulation FD's mandate for prompt public disclosure of material information, many still disclaim a level playing field for analysts (Morgenson 2005, SIA 2005). Constituents assert the problem is not that material information is being privately disclosed, but that the public disclosure of such information suits only specific analysts.

Personal discussions with sell-side analysts provide insights on how public information differentially impacts the analyst. First, an understanding of analyst's incentives is necessary. Under the regulatory environment considered in this study, much of an analyst's compensation derives from commissions attached to order flow. The largest order flows come from institutional investors, and as such analysts compete for institutional order flow. Analysts differentiate themselves in the eyes of institutional investors as preferred information providers by developing niche expertise.

For example, consider two analysts competing for order flow. One analyst specializes in supply chain while another specializes in foreign markets. Analysts gather private information on their respective niches, which, when combined with manager specific information during the conference call, becomes a particularly valuable information bundle for institutional investors. Indeed, the answer managers provide to the supply chain analyst about a supplier relation is of little value to the analyst seeking information on foreign sales prospects, but is critical for the supply chain analyst in maintaining his niche expertise. The notion that publicly provided information is complementary to individuals conditional on their existing private information is modeled in Kim and Verrecchia (1997) and empirically tested by Barron et al. (2005) in the context of securities markets. The same intuition applies here for sell-side analysts competing in the market for information.

While analysts provide in their reports mapping of their information bundles into earnings forecasts and stock recommendations, those mappings are not particularly important for institutional investors. As sophisticated investors, institutions employ their own analysts to perform these mappings and use sell-side analysts to provide critical valuation inputs in the form of information bundles. Surveys of institutional investors confirm these claims. Institutions value a sell-side analyst's industry expertise and access to management (i.e. the information bundle inputs) much more than the sell-side analyst's earnings forecasts and stock recommendations (Johnson 2005).

Since institutions place little weight on the analyst's ultimate stock recommendation, but do value an analyst's access to management, an analyst's incentives can drive positively biased stock recommendations. Favorable stock recommendations please managers, which in turn allow the analyst access to critical manager provided information that is valuable to the analyst's most lucrative client. The SEC's concern resides with the unsophisticated investor who relies exclusively on stock recommendations and cannot reasonably incorporate the analyst's incentives when evaluating a stock recommendation.

Empirical Evidence of Managerial Discrimination. Evidence of specific discriminatory actions by managers has remained largely anecdotal because discrimination itself is generally unobservable (Francis et al. 2004). As a result, the empirical literature has focused on investigating the existence of managerial discrimination indirectly; this has generated mixed results. Francis and Philbrick (1993) provide evidence consistent with analysts fearing retribution for unfavorable stock recommendations by showing that such analysts compensate by issuing optimistic earnings forecasts.

Under the assumption that higher earnings forecasts help cultivate relationships with management, Huang et al. (2005) examine changes in earnings forecast accuracy for analysts who issue boldly favorable (unfavorable) annual earnings forecasts. They find that boldly favorable (unfavorable) analysts experience deterioration (improvement) in future earnings forecast accuracy and interpret their results as inconsistent with the discrimination hypothesis. Ke and Yu (2005) suggest that managers prefer forecasts that help them beat consensus estimates and investigate analysts who issue annual "walk-down" forecasts or pessimistic quarterly earnings forecasts.[1] They find that such analysts have more accurate future earnings forecasts compared to other analysts, and interpret their results as consistent with the discrimination hypothesis.[2]

[1] Walk-down forecasts are those annual earnings forecasts that are optimistic early in the year and pessimistic immediately prior to the earnings announcement (Richardson et al. 2004).

[2] Whether managers prefer optimistic or pessimistic earnings forecasts is an unresolved empirical question. The results from Huang et al. (2005) and Ke and Yu (2005) imply that managers prefer, and reward analysts for, earnings forecasts that ultimately allow them to beat the consensus forecast. However, Francis et al. (2004) show that, on average, firms report earnings *below* consensus for much of the sample time period covered in both Huang et al. (2005) and Ke and Yu (2005). Such an outcome is consistent with managers preferring optimistic forecasts, as modeled by Lim (2001).

Each of the aforementioned studies looks for evidence of managerial discrimination prior to the passage of Regulation FD, which limits the generalizability of the results to the current regulatory regime. Chen and Matsumoto (2005) begin to fill this void by investigating changes in analyst relative earnings forecast accuracy for analysts who downgrade versus upgrade the firm's stock both pre and post Regulation FD. They show that downgrading analysts have relatively poorer one-quarter-ahead earnings forecast accuracy compared with upgrading analysts, but only in the pre-FD era. Their results are therefore consistent with Regulation FD curbing discrimination, at least with respect to manager provided information about one-quarter-ahead earnings. However, their use of earnings forecast accuracy changes as indirect discrimination proxies make it difficult to distinguish between failed attempts at discrimination and the absence of discrimination post-FD.[3] Further, their lack of discriminatory evidence post-FD is contrary to growing outcry from analysts and regulators that discrimination persists (Mayo 2006, Lowengard 2006, Morgenson 2005, SIA 2005, Cox 2005, Davis 2004, Kelly 2003, Solomon and Frank 2003).

I build on prior literature by utilizing a dataset of earnings conference call transcripts to investigate one specific type of managerial discrimination: differential conference call participation. Investigating this specific type of discrimination is important for a number of reasons. First, management discrimination in the form of differential analyst access to management during the conference call is measurable, which allows for more direct and powerful tests of the discrimination hypothesis. Second, the availability of

[3] For example, analysts may have searched harder post-FD for idiosyncratic information and covered fewer firms more intently as brokerage houses cut back research budgets (Mohanram and Sunder 2003). Differential effort in the post-FD period by analysts could potentially be enough to offset the effects of discrimination.

conference call transcripts has come about largely as a result of Regulation FD. As such, results based on conference call data are relevant to the current regulatory environment. Third, and most importantly, the SEC has targeted this specific type of discrimination for potential legislation (Cox 2005). However, the SEC's concerns are based on anecdotes and analyst surveys. Anecdotes are not evidence of a systematic problem. Analyst survey evidence is potentially biased because analysts have incentives to claim that managers discriminate because regulatory intervention could reduce their information search costs. Systematic empirical evidence on whether managers discriminate among analysts through conference call participation could be an important input to the legislative process.

If SEC concerns are warranted because managers do discriminate among analysts during earnings conference calls, then the following hypothesis obtains:

H1: The probability that an analyst is allowed to participate on a conference call is increasing in the favorableness of the analyst's view of the firm.

The discrimination hypothesis is premised on managerial preferences for high stock prices. Therefore, the extent to which a manager discriminates among analysts should vary systematically with the manager's incentives to maintain a high stock price. This leads to the following hypothesis:

H2: The extent of discrimination among analysts is higher (lower) for managers with higher (lower) incentives for high stock prices.

Another underpinning of the discrimination hypothesis is that analysts rely on management for information. In situations where an analyst has alternative sources of information, such as general media coverage or information transfer from other firms, suppliers, and customers, they may not need much information from management.

Discrimination against unfavorable analysts who do not rely heavily on management provided information will likely have little effect on changing an unfavorable analyst's view of the firm. As a result, discrimination should be more pronounced in situations where analysts need to rely more heavily on management.[4] Stated formally:

> *H3: The extent of discrimination among analysts is higher (lower) when analysts rely more (less) heavily on management for information.*

2.3 Sample selection, research design and variable measurement

Sample

The empirical analysis utilizes quarterly earnings conference call transcript data obtained from the Thomson Financial StreetEvents database. StreetEvents is a calendar data service that allows subscribers to track upcoming information events of publicly traded firms, including earnings conference calls, shareholder meetings, IPO lockout expirations and other corporate events. Additionally, the database maintains a history of information events, including verbatim earnings conference call transcripts, shareholder meeting transcripts, press releases, and SEC filings.

Sample transcripts fall between January 2002 and December 2004.[5] All firm-quarter observations occur subsequent to the passage of Regulation FD in 2000, which provides a strong setting for testing the discrimination hypothesis. Analysts have few substitutes for obtaining *material* private information from managers outside of the conference call. The proscriptions of Regulation FD require prompt documentation and dissemination of material information privately conveyed to analysts, which becomes cost

[4] Analysts who need to rely little on management should still seek participation on the conference call. Accessing information directly from management should always minimize information search costs relative to other substitute information sources, even if other information sources are not prohibitively costly.
[5] The earliest transcripts available on StreetEvents are from 2001, however the year is sparsely populated.

prohibitive as the number of analysts grows, making the conference call venue more cost effective for managers.[6] Consequently, under Regulation FD all interested parties can listen to the public dissemination of material information during the conference call, but managers still retain flexibility over who is allowed to ask questions. Managers differentially allow analysts to ask questions by either selectively providing analysts with the question call-in phone number or by simply passing over particular analysts in the question queue.

I identify an initial sample of 27,642 quarterly earnings conference call transcripts that have related coverage in I/B/E/S for the same fiscal quarter end. I use I/B/E/S to identify a population of analysts potentially interested in participating on a firm's quarterly earnings conference call. From this initial sample I require each analyst-firm-quarter observation to have both an outstanding earnings estimate and an outstanding stock recommendation. Outstanding earnings forecasts must be issued during the year preceding the fiscal quarter end date to help ensure the analyst is actively covering the company. I also require each analyst to have attributes measurable over the most recently completed calendar year end. These attributes, discussed more completely below, capture an analysts' experience, effort, and ability relative to other analysts following the firm. The cumulative effect of these requirements results in a final sample of 19,677 earnings conference call transcripts and 146,708 analyst-firm-quarter observations. These observations represent 2,874 unique firms and 4,251 unique analysts from 402 unique brokerage houses.

The filtering procedures remove analyst observations with severely stale earnings forecasts, firms followed by fewer than two analysts during the prior calendar year, and

[6] SIA (2001) provide survey evidence consistent with this notion. Surveyed sell-side analysts reported fewer one-on-one discussions with management after the implementation of Regulation FD. Brown et al. (2005) documents a dramatic increase in earnings conference calls since Regulation FD.

analysts who were not on I/B/E/S during the prior calendar year. Compared with the initial sample, the final sample is comprised of analysts who follow the firm more intently, who are competing against other analysts for managerial access, and who have had more time to establish relationships with company management. This resulting set of analysts should have a strong desire to participate on the firms' conference calls.[7]

I then use the I/B/E/S broker translation files to obtain each analyst's name and brokerage-house affiliation. Using the analysts' name and affiliation from I/B/E/S, I search for the corresponding name and affiliation of the analyst in the related conference call transcript. I identify I/B/E/S analyst *i* covering firm *j* at quarter *t* as "participating" if he/she asks a question on the earnings conference call of firm *j* at quarter *t*. From the conference call transcript, I also obtain the names and titles of the corporate participants, the names and affiliations of all non-corporate participants (a subset of which are the I/B/E/S analysts), the order in which each non-corporate participant appears on the conference call, the number of words spoken during the briefing portion and question-and-answer portion of the conference call, the number of words spoken during the entire conference call, and the number of words exchanged between each non-corporate participant and management.

Table 1 provides descriptive statistics for the sample. Panel A shows that there is some growth in the number of firm-quarter and analyst-firm-quarter observations over

[7] The ideal sample would be the set of analysts who attempted to ask a question during the conference call, regardless of whether management actually allowed the question to be asked. Unfortunately, this is unobservable. Even if such a set of analysts was obtainable, it is unclear whether analysts with unfavorable views, anticipating management's actions, would even attempt to ask a question on the call. Analysts not attempting to ask question for fear of management discrimination is precisely the behavior the SEC and legislators are interested in preventing.

time, consistent with the StreetEvents database gaining popularity.[8] Panel B shows the concentration of observations across industries. There is some clustering in the computer and financial industries, which make up 19 percent (22 percent) and 11 percent (12 percent) of the sample firm-quarters (analyst-firm-quarters). No other industry makes up more than 10 percent of the sample. Panel C shows that 54 percent (44 percent) of firm-quarter observations come from the NYSE (NASDAQ) stock exchanges.

Research design and variable measurement for testing H1

Testing the discrimination hypothesis involves modeling the probability that analyst i following firm j at quarter t participates on the earnings conference call by asking a question. I therefore estimate the following logistic regression model:

$$\begin{aligned} OnCall_{i,j,t} = {} & \beta_0 + \beta_1 SBuy_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4 SSell_{i,j,t} \\ & + \beta_5 Open_{i,j,t} + \beta_6 NumAnalyst_{i,j,t} + \beta_7 AllStar_{i,j,t} \\ & + \beta_8 PriorAcc_{i,j,t} + \beta_9 FirmExp_{i,j,t} + \beta_{10} GenExp_{i,j,t} + \beta_{11} Inds_{i,j,t} \\ & + \beta_{12} ForFreq_{i,j,t} + \beta_{13} BrokerSize_{i,j,t} + \beta_{14} Companies_{i,j,t} \\ & + \beta_{15} PriorOnCall_{i,j,t} + \beta_{16} RecHorizon_{i,j,t} + \upsilon_{i,j,t} \end{aligned} \quad (1)$$

The dependent variable, *OnCall*, is an indicator variable for conference call participation that equals 1 if the analyst asks a question on the conference call and zero otherwise. The first four independent variables use stock recommendation levels to proxy for how favorably the analyst views the firm. The use of stock recommendations is consistent with SEC and anecdotal claims that cite unfavorable stock recommendation levels as reasons for management discrimination (Cox 2005, Solomon and Frank 2003).

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[8] Coverage of a firm by StreetEvents is driven by subscriber demand. Therefore, relative to all public firms, the sample firms are of interest to the individual and institutional investors that subscribe to StreetEvents. Results from analyzing this sample may not generalize to other firms where investor interest is not high. However, this sample suits the research question nicely since regulators are likely to be less concerned with discrimination in situations where there is little interest in the stock.

Sbuy, Buy, Sell and SSell are indicator variables that identify when the analyst's most recent stock recommendation level prior to the conference call is strong buy, buy, sell and strong sell, respectively.[9] If H1 is true and managers allow conference call participation as an increasing function of the analyst's view of the firm, then strong buy recommendation analysts should be more likely than buy recommendation analysts to ask questions; buy recommendation analysts should be more likely to participate than hold recommendation analysts, and so on. Equation (1) models the impact of the analyst's recommendation incremental to the base case of a hold recommendation, resulting in the following predictions: $\beta_1 > \beta_2 > 0$ and $0 > \beta_3 > \beta_4$.

The discussion thus far only considers the analyst's view of the firm. However, a well-specified model should include other factors that potentially constrain analysts' participation. I consider two factors. First, conference calls are costly to the manager in the sense that they take time away from their day to day managing of the firm. As such, conference calls cannot reasonably be expected to answer every question of every analyst. Managers generally preset the amount of time they will allow for the entire conference call and also select the amount of time they will devote to answering analyst questions. The variable *Open* proxies for the time allotted for answering analyst questions during the conference call and is measured as the ratio of the time spent on the conference call answering questions to the total length of the conference call. Higher values of *Open* mean more chance for an individual analyst to speak with management, which leads to the

[9] I use indicator variables at each I/B/E/S recommendation level to allow for discrimination within firms and across firms. Within firm discrimination represents the situation where a manager faces analysts with disperse recommendations and chooses the more favorable analysts for participation. Discrimination across firms represents the situation where a manager faces analysts with the same recommendations on the firm (i.e., no dispersion in analysts' forecasts). Discrimination in this setting would imply that the manager facing analysts with unanimously unfavorable views would allow less participation from analysts following the firm than the manager facing analysts with unanimously favorable views of the firm. Results are not sensitive to this design choice, as documented in the sensitivity tests.

prediction that β_5>0. Additionally, if there is a fixed supply of time for questions, the more analysts there are covering the firm, the less likely it is that any individual analyst will ask a question. This implies a negative relation between the probability of participation and the number of I/B/E/S analysts, *NumAnalyst,* covering the firm (β_6<0).

In addition to participation constraints, an individual analyst's quality should increase both the analyst's desire to participate and the manager's decision to allow such participation.[10] Controlling particularly for an analyst's desire to participate is critical for drawing correct inferences with respect to the analyst's view of the firm. Because I do not have data that identifies with certainty the analysts who *attempted* to participate, my empirical tests are ultimately joint tests of both the discrimination hypothesis and tests of analyst's participation desire. In regression model (1) I attempt to rule out analyst participation as a competing hypothesis by including control variables for analyst quality, which should correlate with their unobservable desire to participate.

I define analyst quality as a combination of an analyst's ability, experience and effort. Prior research shows that these characteristics determine forecast accuracy (Clement 1999) and the extent that the analyst will search for private information that results in bold earnings forecasts (Clement and Tse 2005). I assume these same characteristics proxy for analyst quality in providing information-intermediary services to the market.

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[10] Poor-quality analysts may expose their quality type on the conference call if they ask a question, and therefore may avoid speaking publicly out of concern for their own careers. Of course, the market could infer their quality type to some extent by noting their non-participation, but the poor-quality analyst is unlikely to facilitate the revelation process by directly exposing themselves. Likewise, managers acting in the best interest of the shareholders would not want to waste time with poor quality analysts, whose questions could potentially confuse investors or take time away from answering more pertinent questions.

To capture the firm-specific variation in analyst characteristics, which should influence management's selection of participating analysts, I scale each of the continuous characteristic variables to range from 0 to 1 using a transformation that preserves the relative distances among each characteristic's measures for firm j in quarter t.[11] Doing so also allows for ease of comparison of regression coefficients across analyst characteristics and straightforward use of the odds ratio for interpreting logistic regression results. The relative measures of the analyst characteristics take the form

$$Characteristic_{i,j,t} = \frac{Characteristic\_raw_{i,j,t} - \min(Characteristic\_raw_{j,t})}{\max(Characteristic\_raw_{j,t}) - \min(Characteristic\_raw_{j,t})},$$

where high $Characteristic_{i,j,t}$ values indicate that analyst i scores high on that characteristic relative to other analysts who follow firm j in quarter t.

If managers choose the high quality analysts and high quality analysts have a higher propensity to attempt to participate, then analysts who are research all-stars (*AllStar*), analysts who were relatively more accurate in predicting the firm's prior quarter earnings (*PriorAcc*), analysts with relatively more general (*GenExp*) and firm specific experience (*FirmExp*), analysts who provide relatively more forecasts of earnings (*ForFreq*) and analysts with relatively more resources available to them (*BrokerSize*) should all have a higher probability of being on the call.[12] These predictions should manifest as $\beta_7>0$, $\beta_8>0$, $\beta_9>0$, $\beta_{10}>0$, $\beta_{12}>0$ and $\beta_{13}>0$. On the contrary, analysts who cover relatively more industries (*Inds*) and firms (*Companies*) develop less expertise and

[11] For example, if a manager is interested in entertaining questions from the most experienced analyst, he will choose the most experienced analyst from the group of analysts that follow the firm. The experience level of that analyst relative to the entire cross-section of analysts is less likely to influence the manager's participation choices.

[12] See Appendix 1 for more complete variable descriptions.

have less time to expend with respect to any particular firm. These analysts should be less likely to participate on the call, which would yield β_{11}<0 and β_{14}<0.

The relationship an individual analyst has with firm management should also influence the probability of participation on the conference call. I proxy for this unobservable relationship by identifying whether the analyst has participated on a firm's conference call in the past (*OnCallPrior*) and expect β_{15}>0. Finally, as modeled by Hayes (1998) and empirically demonstrated by McNichols and O'Brien (1997), analysts are likely to lose interest and gather less information in stocks for which they hold unfavorable views. If interest in a stock is correlated with the level of the stock recommendation, failure to control for such interest could yield spurious inferences regarding discrimination. To the extent interest is not controlled for via the previously discussed analyst quality variables, I include the period of time since the analyst made his/her stock recommendation (*RecHorizon*). I assume that the more stale the recommendation, the higher the probability the analyst has dropped coverage and will not be seeking participation on the conference call. This implies β_{16}<0.

To summarize, equation (1) models the determinants of conference call participation. Evidence on discrimination as posited in H1 is assessed by comparing the coefficients on stock recommendation levels, while controlling for other determinants of conference call participation.

2.4 Results for H1

Descriptive and Univariate Results

Table 2 Panel A provides general descriptive statistics at the firm level. The average firm has total assets of \$11.4 billion, a market capitalization of \$6.0 billion, a market to book ratio of 3.6 and a median quarterly return on assets of about 1 percent. Institutions hold an average of 58.8 percent of the firm's outstanding stock and managerial stock option wealth changes by an average of $519,000 for a 1 percent change in stock price. There is substantial variation in each of the measures, consistent with the sample representing of a broad cross-section of firms, managers, and institutional influence.

Turning to conference call characteristics, the median number of corporate participants (*CorpCount*) is 3, which are typically the CFO, CEO and Director of Investor Relations. At the median, managers take questions from 9 non-corporate participants (*NonCorpCount*).[13] The number of I/B/E/S analysts covering the firm (*NumAnalyst*) ranges from 3 to 10 between the first and third quintiles, with 6 analysts covering the firm at the median. Three I/B/E/S analysts (*IBESonCall*) participate on the median conference call, with an interquartile range from 2 to 6. Eighty-eight percent of all conference calls have at least one I/B/E/S analyst participating (*IBESonCallDum*). Conference calls last an average of 52 minutes, and vary from about 40 minutes to just over an hour at the first and third quartiles. On average, 55 percent of the call is dedicated to answering questions from analysts (*Open*).

The average stock recommendation of the I/B/E/S analysts following the firm (*MarketRec*) is 2.42, compared with 2.32 for the I/B/E/S analysts who are actually allowed to participate on the conference call (*OnCallRec*). Since I/B/E/S codes strong buy recommendations at 1 and strong sell at 5, larger average recommendation values are less favorable. Thus, consistent with managerial discrimination, the average stock

[13] Non-corporate participants include I/B/E/S analysts who cover the firm, other I/B/E/S analysts who do not cover the firm directly, non-I/B/E/S sell-side analysts, bankers, institutional investors, and occasionally individual investors.

recommendation of the analysts participating on the call are more favorable than the underlying market recommendation of all analysts (t = 26.77, p<.001).

The first two columns of Panel A of Table 3 provide descriptive evidence on the pooled sample of analysts. On average, 38 percent of analysts participate on a conference call (*OnCall*), and 58 percent of analysts participated on a prior conference call (*OnCallPrior*). The most common stock recommendation is hold, followed by buy, strong buy, sell and strong sell. The distribution of stock recommendation levels is consistent with other research (Chen and Matsumoto 2005, Barber et al. 2005).

The remaining columns of Table 3 group analysts by whether they participated on the conference call or not. H1 posits that managers will allow analysts with more favorable recommendations on the call. Consistent with this notion, analysts who participate on the call have statistically higher (lower) percentages of buy and strong buy (sell and strong sell) recommendations. Participating analysts are generally of higher quality. In particular, participating analysts are statistically more often all-star analysts (*AllStar* = 22 percent vs 15 percent), have better relative prior forecasting accuracy (*PriorAcc* 0.71 vs 0.69), have relatively more firm-specific experience (*FirmExp* = 0.48 vs 0.45), make relatively more frequent forecasts (*ForFreq* = 0.44 vs 0.41), and are employed by relatively larger brokerage houses (*BrokerSize* = 0.36 vs. 0.33). Additionally, participating analysts have issued their recommendations more recently (*RecHorizon* = 274 vs. 313) and have been on prior conference calls more frequently (*PriorOnCall* = 81 percent vs. 45 percent).

These descriptive comparisons are also consistent with the correlations in Table 3 Panel B. In particular, the Spearman rank correlations show that being on a conference call is positively associated with the analyst's view of the firm as proxied by stock recommendation levels (*IBESRec*, ρ =-0.085, p<.001).[14] Being on a call is positively related to how much time is allotted to taking questions (*Open*, ρ =0.17, p<.001) and negatively related to how many analysts compete for management's time (*NumAnalyst*, ρ =-0.087, p<.001). Participating on the call is positively associated with high quality analyst characteristics like being an all-star (*AllStar*, ρ =0.087, p<.001), being a better earnings forecaster (*PriorAcc*, ρ =0.041, p<.001), forecasting more frequently (*ForFreq*, ρ =0.050, p<.001), having more firm experience (*FirmExp*, ρ =0.041, p<.001), having more general experience (*GenExp*, ρ =0.014, p<.001), and working for a larger brokerage house (*BrokerSize*, ρ =0.057, p<.001).

Contrary to expectations, the number of companies followed by the analyst is increasing in conference call participation (*Companies*, ρ =0.015, p<.001). Consistent with expectations, an analyst's prior conference call participation is positively associated with current conference call participation (*OnCallPrior*, ρ =0.355, p<.001), and participation is decreasing in the staleness of the recommendation (*RecHorizon*, ρ =-0.092, p<.001).

Combined, the univariate relations in both panels of Table 3 are generally consistent with the H1 and the related predicted differences with respect to analyst characteristics. However, the univariate differences across stock recommendations and correlations coefficients are not particularly large. To better assess economic significance

[14] The correlation between conference call participation and stock recommendations is negative because I/B/E/S codes the most favorable recommendations (strong buy) as 1 and the most unfavorable recommendations (strong sell) as 5. So, higher values of *IBESRec* are less favorable, and participation is increasing the favorableness of the stock recommendation when the correlation is negative.

and lend credence to the univariate evidence while controlling for other factors, I turn to the multiple logistic regression analysis.

Multivariate Results

Table 4 Panel A provides the regression results, and shows the model has reasonable fit with a pseudo R^2 of 14.9 percent and 70.0% correct classification rate.[15] Consistent with the concerns of the SEC and analysts, the probability that an analyst participates on the conference call is increasing in the stock recommendation. The coefficient estimates on the stock recommendations represent the incremental probability of conference call participation relative to a hold recommendation. Both *SBuy* (0.500, p <.001) and *Buy* (0.356, p <.001) are significantly positive, with strong buy recommendations increasing the probability of participation more than buy recommendations (difference = 0.144, p <.001). Similarly, *SSell* (-0.274, p <.001) and *Sell* (-0.174, p <.001) are significantly negative, with strong sell recommendations decreasing the probability of participation more than sell recommendations (difference = 0.100, p = 0.060). Using odds ratios to interpret the difference between strong sell and strong buy recommendations, an analyst with a strong buy recommendation has participation odds more than twice $(e^{(\beta_1-\beta_4)} = e^{(0.500+0.274)} = 2.17)$ those of an analyst with a strong sell recommendation.

To provide more intuition for the economic magnitude of this effect, Panel B of Table 4 plots the marginal probability effects of stock recommendations for two types of analysts. The first type of analyst (Type 1) has sample average characteristics on all

[15] The calculation of correctly classified observations assumes each analyst has an equal probability of participating versus not participating. Using the sample average of a 38.1 percent chance of participation yields a correct classification percentage of 68.6 percent. Additionally, the area under the receiver operator characteristic (ROC) curve for the estimation of model (1) is .753, suggesting reasonable predictive power.

continuous variables, was not an all-star analyst (*AllStar*=0), and participated on a previous conference call of the firm (*OnCallPrior*=1). The predicted participation probability for a Type 1 analyst with a strong sell recommendation is 39 percent, and jumps 19 percentage points to 58 percent for holding a strong buy recommendation. The upward slope of the graph shows the probability of participation is increasing in the stock recommendation of the analyst. The largest change in predicted probability results when stock recommendations change from hold to buy compared to changes in any other adjacent levels.

A second type of analyst (Type 2) is exactly the same as the first type, but is an all-star analyst (*AllStar*=1). The pattern is similar to the first type of analyst, however the Type 2 analyst is rewarded for all-star status by having a higher predicted participation probability of about 10 percent across all stock recommendation levels. A strong sell recommendation yields a predicted participation probability of 49 percent, which is 19 percent lower than the 68 percent probability for a strong buy recommendation.

All other regression coefficients are statistically significant in the predicted direction except the coefficient on *GenExp*, which is significantly negative, suggesting that analysts with relatively more general experience have a lower probability of participating on the conference call. Perhaps analysts with lots of general experience need less direct information from management or have established reputations that do not benefit at the margin from sparring with management during the conference call.

As expected, an analyst has a better chance of getting on the conference call when firms dedicate more time to answering analyst questions (*Open*=2.131, p<.001) and when there are fewer analysts competing for management's time (*NumAnalyst*=-0.031, p<.001).[16] The participation odds are more than five times higher for analysts who previously participated on a conference call compared to those who did not, suggesting that a prior relationship with management is very important in obtaining access to the call. With respect to analyst quality, the most accurate analyst has 1.321 times (p<.001) higher participation odds than the least accurate analyst. More firm experience, more forecast frequency, working for a larger brokerage house and covering fewer companies all increase the odds of being on the conference call. These results are consistent with both firms allowing the highest quality analysts to participate on the conference call and with low quality analysts not seeking participation.

Sensitivity Tests

Analyst favorableness on a relative basis. Equation (1) captures discrimination within and across firms by using indicator variables for analyst stock recommendation levels. To isolate the within firm effects, I measure analyst stock recommendations relative to other analysts following the firm, (*RelRec*) and re-estimate equation (1). As shown in Table 5, the coefficient on *RelRec* is a significantly positive 0.460. This implies that the most favorable analyst following the firm has participation odds 1.58 times higher than the least favorable analyst. These results yield similar inferences to those reported in Table 4, although the ability to compare differences across specific stock recommendation levels is removed.

Differences model for correlated omitted variables. Equation (1) potentially suffers from unknown or unmeasurable correlated omitted variables. To the extent such variables are constant over time, estimating a differences version of equation (1) by fiscal quarter helps alleviate the correlated omitted variables problem. To estimate a differences

[16] Inferences are unchanged if the raw number of question and answer minutes is used instead of *Open*.

model, I identify the subsample of consecutive quarterly conference calls so that current and prior conference call participation can be measured for each analyst. I then require the analyst to make a recommendation change or reiteration during the period between the current and prior quarter conference call. This sampling procedure yields a total of 16,535 analyst-firm-quarter observations, comprised of 7,501 analysts who did participate on the prior period conference call ($OnCall_{i,j,t-1}=1$), and 9,034 who did not participate on the prior period conference call ($OnCall_{i,j,t-1}=0$). I then estimate the following model in order to assess how recommendation changes in the form of upgrades and downgrades impact the probability of an analyst participating on the conference call:

$$OnCall^{s} = \beta_0^{s} + \sum_{m=1}^{10} \beta_m^{s} Upgrades + \sum_{n=11}^{20} \beta_n^{s} Downgrades + \beta_{21}^{s} NumAnalyst + \beta_{22}^{s} Open + \varepsilon^{s} \quad \text{(1a)}$$

where *s* is either the ($OnCall_{i,j,t-1}=0$) sample or the ($OnCall_{i,j,t-1}=1$) sample, *Upgrades* are indicator variables for each of the ten potential types of upgrades (i.e., *SSell* to *Sell*, *Sell* to *Hold*, etc.), *Downgrades* are indicator variables for each potential type of downgrade, *NumAnalyst* and *Open* are as previously defined, and analyst-firm-quarter subscripts are omitted for brevity. Analyst characteristic variables are not included because they are not expected to change from quarter to quarter, yielding differences of zero. No explicit control is included for the staleness of recommendation (which proxies for analyst interest in the stock) because both recommendation changes and reiterations must occur within the approximate three month period between consecutive quarterly earnings conference calls.

If upgrades (downgrades) are pleasing (displeasing) to managers, then upgrades (downgrades) should increase (decrease) the participation probability. Since recommendation reiterations (i.e., confirmed no-change recommendations) are the base case, discrimination would imply positive (negative) coefficients on β_1 (β_{11}) through β_{10}

(β_{20}). As before, time and participation constraints should yield negative (positive) coefficients on *NumAnalyst* (*Open*).

The results are presented in Panel A of Table 8. Across both analyst subsamples, all statistically significant coefficients are as expected, consistent with managers rewarding (punishing) analysts who upgrade (downgrade). However, there are two key exceptions. First, among the set of analysts who did not participate on the prior conference call, upgrades from *SSell* to *Hold* decrease the analysts' participation probability relative to a reiterating analyst. In fact, only upgrades the ultimately result in recommendation levels above *Hold* please management enough to warrant statistically significant increased conference call access.

Second, across both subsets of analysts, downgrades from *SBuy* to *Buy* increase the analyst's participation probability relative to a reiterating analyst. Thus, downgrading analysts can retain preferential conference call access so long as the ultimate recommendation level remains above a *Hold*. The apparent importance of the *Hold* recommendation level as a threshold for both upgrade and downgrade importance is consistent with Panel B of Table 4. There, the largest participation probability increases (decreases) obtain when analyst recommendation levels move above (down to) the *Hold* recommendation.

Combined, these results generally suggest that managers discriminate based on recommendation changes, but also that all upgrades (downgrades) are not equally pleasing (displeasing) to managers. These findings are inconsistent with Chen and Matsumoto's (2005) conclusions that managers do not discriminate based on analyst upgrades and downgrades in the post-FD period.

Using indicator variables for each type of upgrade and downgrade results in sparse population for some recommendation change combinations. As a result, insignificant results on some recommendation change combinations in Panel A of Table 6 could result from low power. To provide further support for the overall assertion that positive (negative) recommendation changes result in more (less) conference call access, I calculate a continuous recommendation change variable for each observation as *RecChange* = $Recommendation_{i,j,t}$.- $Recommendation_{i,j,t-1}$ where *Recommendation* equals 5 for strong buy, 4 for buy, 3 for hold, 2 for sell and 1 for strong sell. Thus, upgrades have positive values and downgrades have negative values. I then replace all upgrade and downgrade indicator variables equation (1a) with the continuous recommendation change measure. If upgrades (downgrades) increase (decrease) the probability of participating, I expect a positive relation positive relation between the recommendation change and participation. Panel B of Table 6 reveals results consistent with this expectation. In particular, I obtain positive and significant recommendation change coefficients in both subsamples, consistent with managerial discrimination.

Insufficient control for analyst interest in the firm. In Panel A of Table 4, the variable *RecHorizon* is significantly negative (-.001, p<.001) as expected, suggesting that the more stale the recommendation, the less likely an analyst is to participate.[17] *RecHorizon* attempts to control for analyst interest in the stock, which is important to the extent that interest is correlated with stock recommendations (McNichols and O'Brien 1997, Hayes 1998). To provide further assurance that lack of interest in the stock does not drive the main discrimination results, I re-estimate equation (1) using only the 98,174

[17] Similar results obtain when I use the staleness of the analyst's outstanding quarterly earnings forecast instead of stock recommendation.

analyst-firm-quarter observations where an earnings forecast was issued subsequent to the conference call. This increases the likelihood that the analyst was interested in the stock at the most recent conference call. Results (not reported) are consistent with Table 4. The probability of participating remains increasing in the stock recommendation, and strong buy recommendation analysts have participation odds double those of the strong sell recommendation analysts.[18]

Lack of independence across observations. The observations used to estimate equation (1) in Table 4 come from a pooled cross-section where individual observations are not independent. The standard errors used for test statistics are robustly estimated and are clustered by firm, under the assumption that firm characteristics and managerial actions will impact analyst participation. Thus, the standard errors allow for a lack of independence across analysts covering a given firm, and assume independence across groups of analysts by firm. Despite the firm clustering, the pooled cross-section still contains multiple observations of the same firm, which violates the independence assumption. To address this potential problem, I re-estimate equation (1) using the Fama MacBeth (1973) procedure. I estimate Equation (1) separately by calendar-quarter thereby ensuring that only one firm is represented in the cross section. Then, I average the coefficients and generate a t-statistic from the individual calendar quarter coefficients. Results, reported in column B of Table 7 are very similar to those reported in Table 4 in significance and magnitude, with the exception *BrokerSize (GenExp)*, which are both insignificant at conventional levels. Additionally, the coefficients on *SBuy*, *Buy*, *Sell*, and *SSell* are of the predicted sign (statistically significant) in 12 (12), 12 (12), 10 (6), and 11

[18] If discrimination results in unfavorable analysts dropping coverage after the conference call, this sampling procedure would result in lower variation in the outstanding recommendations at the time of the conference call, which biases against finding support for the discrimination hypothesis.

(7) of the quarterly regressions, respectively. These results suggest the results in Table 4 are not driven by any individual fiscal quarter.

Another potential lack of independence results from having multiple observations of the same analyst in the cross section and over time. To assess whether this possibility affects any inferences, I re-estimate equation (1) again using the Fama MacBeth (1973) procedure and randomly select one observation for each analyst in the calendar quarter cross section. This estimation procedure results in calendar quarter samples with unique firm-analyst combinations, removing independence concerns at both the firm and analyst level. Results, reported in Column A of Table 7 are consistent with those presented in Table 4, except that the coefficient on *GenExp*, *FirmExp* and *BrokerSize* are insignificant. The model has similar average explanatory power and the strong buy recommendation analysts retain participation odds more than double those of the strong sell recommendation analysts.

Managerial preferences for pessimistic earnings forecasts. Ke and Yu (2005) provide results consistent with managers rewarding analysts who provide pessimistic forecasts prior to the earnings announcement. If pessimistic analysts tend to have unfavorable forecasts, the previous results could be driven by the failure to account for the pessimism in analyst earnings forecasts. To assess whether forecast pessimism is a correlated omitted variable, I follow Ke and Yu (2005) and add to equation (1) a variable that equals 1 if the analyst's most recent outstanding quarterly earnings forecast is below the consensus forecast, and zero otherwise. Results (not reported) show that adding this variable has a negligible effect on the magnitude and significance of the coefficients reported in Table 4 and inferences remain unchanged. However, the pessimism logit coefficient is positive and significant (0.139, p<.001), implying that pessimistic analysts are more likely to participate on conference calls compared to other analysts. These results are consistent with Ke and Yu (2005), although the effects of forecast pessimism on the odds of participating are an order of magnitude lower than the effects of strong buy or strong sell recommendations.

2.5 Effect of managerial incentives and analyst reliance on management on discrimination extent

Research Design and Variable Development for H2 and H3

The previous section provides evidence consistent with the existence of managerial discrimination among analysts. Estimation of equation (1) provides evidence on the average extent of discrimination by assessing the difference between the coefficients on *SBuy* and *SSell*. If discrimination truly results from managerial actions, as opposed to analyst's differential propensity to seek access, the extent of managerial discrimination should vary in predictable ways. In particular, as stated in H2 (H3), managers should discriminate more when they have the higher incentives for high stock prices (when analysts rely heavily on them for information).

To assess the impact of managerial incentives (analyst reliance) on the extent of discrimination, I re-estimate equation (1) separately by quintile of managerial incentives (analyst reliance). Doing so allows the coefficients in equation (1) to vary across levels of managerial incentives (analyst reliance). To statistically assess whether the extent of discrimination differs between the lowest and highest quintile of managerial incentives (analyst reliance), I estimate the following unrestricted version of equation (1):

$$OnCall = \sum_{q=Low}^{High} \left(\beta_0^q + \beta_1^q SBuy + \beta_2^q Buy + \beta_3^q Sell + \beta_4^q SSell + \sum_{n=5}^{16} \vec{x}^{\,q} \right) + \upsilon \qquad (2)$$

where q is the incentive quintile of the manager (analyst reliance quintile of the analyst) and $\vec{x}$ is the vector of non-stock recommendation level variables and analyst-firm-quarter subscripts are omitted for brevity.

If managers discriminate between *SBuy* and *SSell* analysts more (less) when they have high (low) incentives to maintain high stock prices then H2 predicts $(\beta_1^{Low} - \beta_4^{Low}) < (\beta_1^{High} - \beta_4^{High})$. The differential treatment of analysts could be driven by either rewarding *SBuy* analysts, in which case $(\beta_1^{Low} < \beta_1^{High})$, and/or retaliation against *SSell* analysts, in which case $(\beta_4^{Low} > \beta_4^{High})$. Similarly, if managers discriminate more (less) when analyst reliance is high (low), then H3 also predicts $(\beta_1^{Low} - \beta_4^{Low}) < (\beta_1^{High} - \beta_4^{High})$ driven by $(\beta_1^{Low} < \beta_1^{High})$ and/or $(\beta_4^{Low} > \beta_4^{High})$.

I operationalize managerial incentives for high stock prices when testing H2 through CEO option wealth sensitivities to stock prices. Prior literature suggests managers with high option wealth sensitivities to stock prices take actions to increase accruals in an attempt to maintain high stock prices (Cheng and Warfield, 2005). If discrimination among analysts is another mechanism to keep stock prices high, the discrimination should be more pronounced when managers have higher option wealth sensitivity to stock prices. I measure option wealth sensitivity via Execucomp as the change in the CEO's option wealth sensitivity for a 1 percent change in stock price (Core and Guay, 2002).

I proxy for analyst reliance on management using the extent of institutional holdings. Institutional investors rely on sell-side analysts to provide unique firm-specific information, and survey evidence shows that institutions highly value a sell-side analyst's ability to access company management (Johnson, 2005). Institutions reward analysts that provide them key valuation inputs with commission generating order flow. Since managers understand the pressure analysts face to please institutional clients, managers should discriminate more when institutional holdings are high.[19] I measure institutional holdings (*InstHold*) as of the most recent calendar quarter prior to the firm's fiscal quarter end.

Results for H2 and H3

Panel A of Table 8 reports the results with respect to H2 on managerial incentives. Panel A shows that the difference between *Sbuy* and *SSell* for managers with the highest wealth sensitivity is greater than the difference for managers with the lowest wealth sensitivity (difference = 0.405, p = 0.044). The graph shows that the increase in discrimination is driven primarily by managers preventing questions from strong sell analysts as opposed to catering differentially to strong buy analysts. In particular, the difference between strong sell analysts in the high and low incentive conditions is statistically different than zero (difference = -0.423, p = 0.027). The treatment of strong buy analysts is roughly constant across the high and low incentive conditions, and the difference is not statistically significant (difference = -0.019, p = 0.830).

Panel B of Table 8 reports the results with respect to H3 regarding analyst reliance on management for information. Panel B shows that the difference between *Sbuy* and *SSell* for analysts who rely most heavily on management is greater than the difference for analysts that rely least on management for information (difference = 0.288, p = 0.061). The graph shows that the increase in discrimination is driven primarily through catering more heavily to strong buy analysts (difference = 0.189, p = 0.003). Retaliation against

[19] The indirect effects of institutions on a manager's propensity to discriminate are unclear. If institutions act as monitors and view discrimination as a sign of deeper managerial problems detrimental to firm value, they may act as a deterrent to discrimination. On the other hand, if institutions are on average short-sale constrained, they have incentives to keep the stock prices of their holdings high just like managers do. In such a case they would welcome discrimination.

strong sell analysts plays some role in the overall discrimination difference (difference = -0.099), but the differential treatment of strong sell analysts across conditions is not statistically significant ($p = 0.291$).

Together, the H2 and H3 results confirm the earlier conclusion that managers discriminate by showing that discrimination varies in predictable ways with respect to managerial incentives for high stock prices and the analyst's need to rely on management for information.[20] Interestingly, in both panels of Table 8, discrimination still exists even when incentives and management reliance are low.

2.6 Discrimination conditional on participating on the conference call

Previous sections have attempted to rule out the competing hypothesis that discriminatory evidence obtains from a failure to control for analyst propensity to seek conference call participation. To completely rule out this possibility, this section investigates the treatment of analysts who have been allowed call participation, which ensures an analyst's interest in the stock at the time of the conference call. If managers discriminate based on analyst stock recommendations, evidence should exist even among those analysts participating on the conference call. Such differential analyst treatment might include pushing unfavorable analysts further down the question queue or speaking to the favorable (unfavorable) analyst more (less) during the conference call.

Question Queue Discrimination

Managers can discriminate among analysts by explicitly allowing (denying) favorable (unfavorable) analyst participation. A more subtle way to discriminate is for the

[20] For the alternative hypothesis that analyst interest in the stock drives the observed empirical results, it would have to be the case that unfavorable analysts lose interest more when CEOs have high option wealth sensitivities and when institutional holdings are high. It unclear why this would be the case.

manager to rank the queue of analysts attempting to ask a question in order from most favorable to least favorable and then take questions until the allotted conference call time expires. Queue ordering in this manner increases (decreases) the probability that enough time will remain to hear a question from the favorable (unfavorable) analyst.

To investigate whether managers manipulate the question queue as a method of discrimination, I estimate the following linear regression:

$$\begin{aligned} Queue|OnCall_{i,j,t} = {} & \beta_0 + \beta_1\, SBuy_{i,j,t} + \beta_2\, Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4\, SSell_{i,j,t} \\ & + \beta_5\, AllStar_{i,j,t} + \beta_6\, PriorAcc_{i,j,t} + \beta_7\, FirmExp_{i,j,t} \\ & + \beta_8\, GenExp_{i,j,t} + \beta_9\, Inds_{i,j,t} + \beta_{10}\, ForFreq_{i,j,t} + \beta_{11}\, BrokerSize_{i,j,t} \\ & + \beta_{12}\, Companies_{i,j,t} + \beta_{13}\, PriorOnCall_{i,j,t} + \upsilon_{i,t} \end{aligned} \qquad (2)$$

where:

Queue|OnCall	The order of the analyst's first appearance on the conference call relative to all non-corporate conference call participants. Relative order is calculated as (Total number of non-corporate conference call participants - position of analyst on conference call)/(Total number of non-corporate conference call participants - 1). The last non-corporate participant to ask a question has a value of 0, while the first non-corporate participant to ask a question has a value of 1.

and all other variables are as previously defined. Equation (2) is identical to equation (1), with the following exceptions. This model does not consider participation constraints (*Open* and *NumAnalysts*) because the sample analysts here are, by definition, participating on the call. Additionally, *RecHorizon* is not included in the model because it is meant to capture the unobservable interest the analyst has in the stock. Since the analyst participates on the conference call in this subsample, interest is ensured.

The discrimination hypothesis predictions are identical to equation (1): $\beta_1>0$, $\beta_2>0$, $\beta_1>\beta_2$, $\beta_3<0$, $\beta_4<0$, $\beta_3>\beta_4$. The results in Table 9 provide evidence of discrimination by managerial manipulation of the question queue. In particular, the coefficients on *SBuy* (0.044, p<.001) and *Buy* (0.046, p<.001) are significantly positive, suggesting that strong buy and buy recommendation analysts are dealt with by management before analysts with hold recommendations. The opposite is true for *SSell* (-0.024, p<.001) and *Sell* analysts (-0.017, p=.038), who are statistically lower in the question queue than hold analysts. The difference between strong buy (strong sell) and buy (sell) recommendation analysts is not significant, but the overall tenor of the results points to discrimination increasing in the analysts favorableness toward the firm.[21]

Duration of Manager/Analyst Interaction

If managers cater to the informational needs of favorable analysts more so than unfavorable analysts, then they should spend more conference call time with the former. I assume that the time spent with an analyst sufficiently proxies for the extent of private information transfer from the manager to the analyst, and investigate whether the amount of time spent on the call varies with the analyst's view of the firm. I estimate the following linear regression:

$$\begin{aligned} Time|OnCall_{i,j,t} = {} & \beta_0 + \beta_1 SBuy_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4 SSell_{i,j,t} + \beta_5 UP_{i,j,t} \\ & + \beta_6 DN_{i,j,t} + \beta_7 AllStar_{i,j,t} + \beta_8 PriorAcc_{i,j,t} + \beta_9 FirmExp_{i,j,t} \\ & + \beta_{10} GenExp_{i,j,t} + \beta_{11} Inds_{i,j,t} + \beta_{12} ForFreq_{i,j,t} + \beta_{13} BrokerSize_{i,j,t} \\ & + \beta_{14} Companies_{i,j,t} + \beta_{15} PriorOnCall_{i,j,t} + \upsilon_{i,t} \end{aligned} \tag{3}$$

where:

Time|OnCall The number of minutes managers spend answering questions of the analyst, measured as the number of words spoken to the analyst divided by 150, where 150 is the word count per minute conversion

and all other variables are as previously defined. Equation (3) is identical to equation (2) expect for the change in the dependent variable. Consistent with the discrimination hypothesis in previous sections, I expect $\beta_1>0$, $\beta_2>0$, $\beta_1>\beta_2$, $\beta_3<0$, $\beta_4<0$, and $\beta_3>\beta_4$. Table 10 provides the estimation of equation (3).

[21] Inferences are unchanged if equation (2) is estimated using the Fama MacBeth (1973) procedure.

The results in Table 10 suggest that analysts with strong buy and buy recommendations are allotted more conference call time than hold analysts. In particular, the coefficients on *SBuy* (0.174, $p<.001$) and *Buy* (0.114, $p<.001$) are significantly positive. Sell analysts are not treated significantly differently than the base case hold analyst, but, contrary to predictions, strong sell analysts are spoken to more than the hold analysts (0.135, $p = 0.06$). In fact, the difference in time managers spend with strong sell analysts and strong buy analysts is not statistically significant. Combined, these results are consistent with both managers catering to favorable analysts, and once making the decision to speak with an extremely unfavorable analyst, to debate heavily with them.[22]

2.7 Conclusion

This chapter provides compelling direct evidence that managers discriminate among analysts during earnings conference calls. Using a large dataset of earnings conference call transcripts from 2002 to 2004, I find that the probability of an analyst being allowed to ask a question during an earnings conference call is increasing in the favorableness of the analyst's view of the firm. After controlling for other factors, the odds of an analyst with a strong buy recommendation participating on the conference call are more than twice as high as an analyst with a strong sell recommendation. The extent of discrimination is more (less) pronounced when managers have higher (lower) incentives to maintain high stock prices, and when analysts are more (less) reliant on management as an information source. I also show that, even among the analysts allowed to participate on the conference call, discrimination persists. In particular, the order in which managers accept questions from analysts is increasing in the favorableness of the analyst's stock recommendation.

[22] Inferences are identical when estimating equation (3) using the Fama MacBeth (1973) procedure.

Detecting managerial discrimination through conference call participation requires careful controls for an analyst's propensity to seek participation. Thus, the inferences drawn here are only as valid as the effectiveness of such controls. However, the results consistently provide evidence of managerial discrimination across a number of control specifications.

By measuring discrimination directly using earnings conference call transcripts, I add to the empirical literature on discrimination, where results are mixed perhaps because of reliance on indirect discrimination proxies. My results validate prior anecdotal and survey evidence suggesting that managers discriminate among analysts, and provide evidence on a specific type of discrimination that is currently of concern to legislators (Cox 2005).

Chapter 3: Managerial Discrimination among Analysts and the Market Reaction to Earnings News

3.1 Introduction

This chapter investigates the association between the market reaction to quarterly earnings news and managerial conference call discrimination among analysts. I consider the possibility that the scrutiny of the questions analysts pose to managers during earnings conference calls decreases in the favorableness of the analyst's view of the firm. Under such a scenario, managerial discrimination – the act of granting (thwarting) conference call participation to favorable (unfavorable) analysts – is more likely to result in conference calls that highlight (suppress) positive (negative) aspects of the firm. Discrimination could therefore make good (bad) earnings news look better than (not as bad as) it really is. Understanding how investors view earnings news in the presence of discrimination is important because regulators and the SEC have recently voiced concerns that discrimination during earnings conference calls may ultimately mislead investors (Cox 2005).

I investigate the association between discrimination and the market reaction to earnings news in two steps. I first utilize a random sample of 125 conference call manager-analyst dialogs to ascertain whether the scrutiny of analyst questions varies with the favorableness of the analyst's view of the firm. It is this necessary condition that allows discrimination to become a managerial tool to control the scrutiny managers face during the conference call, and potentially influence market reactions to earnings news.

I find that, on average, question scrutiny is decreasing in the favorableness of the analyst's view of the firm. That is, more favorable analysts ask less scrutinizing questions.

However, this effect only exists for firms that meet or beat expected earnings. When firms miss earnings targets, favorable analysts become just as scrutinizing as unfavorable analysts. This shift in scrutiny is consistent with the survey evidence in Graham et al. (2005) suggesting managers wish to avoid missing earnings targets because of the enhanced level of analyst scrutiny.

I then classify conference calls as discriminating (non-discriminating) when the ratio of the recommendation consensus of analysts participating on the conference call is more (less) favorable than the recommendation consensus of all analysts covering the firm. Discrimination (non-discrimination) proxies for the scrutiny (lack of scrutiny) placed on managers during the question and answer session of the conference call. I examine the market reaction to large and small good news earnings and large and small bad news earnings in the presence and absence of discrimination.

I find that the market reaction to large magnitude good news earnings is amplified when the manager discriminates, potentially consistent with regulatory concerns. I find no discrimination effects with respect to small magnitude good news earnings. The market reaction to both large and small magnitude bad earnings news is also invariant to the conference call discrimination level, consistent with the lack of a relation between question scrutiny and the favorableness of the analyst's view of the firm when a firm misses earnings targets.

The regulatory perspective on discrimination interprets a positive incremental market reaction to good news earnings as unsophisticated investors being fooled into over-reacting to good news earnings. Further investigation of the regulatory perspective reveals that the effect of discrimination on the market reaction to large good news earnings is not concentrated among unsophisticated investors, but instead is equally prevalent for both sophisticated and unsophisticated investors. Additionally, good news firms that discriminate exhibit less post earnings announcement drift than non-discriminating firms. This implies that, on average, discrimination assists the market in digesting the implications of good earnings news as opposed to assisting the manager in overselling those implications.

The results presented here add to the literature in a number of ways. First, it provides initial evidence on one of the potential consequences of managerial conference call discrimination. If discrimination is a strategic choice made by managers as asserted in Chapter 2, assessing its impact on stock prices is an important next step that should be of interest to both market participants and regulators alike.

Second, I add to the literature on strategic managerial disclosure choice in the realm of voluntary disclosure. The unique managerial choice variable in this setting is the audience with which the manager will interact, as opposed to the strategic placement of favorable voluntary information (Schrand and Walther 2000) or optimistic language in an earnings press release (Davis et al. 2006). More specifically, my investigation of discrimination directly adds to the conference call literature, which has generally concluded that conference calls are effective tools for resolving uncertainty about the implications of earnings news (Kimbrough 2005, Tasker 1998b). However, this literature has focused on the effects of hosting versus not hosting a conference call. Since most firms now host conference calls, I extend this literature by investigating the effects of variation *within* conference calls on the discrimination dimension.

Third, I add to our understanding of the interplay between managers and sell side analysts in the conference call setting. Survey evidence by Graham et al. (2005) suggests that one motivation for managers to beat earnings targets is to avoid analyst scrutiny during a conference call. I provide direct empirical evidence validating that analyst behavior varies based on the earnings news.

This chapter proceeds as follows. Section 2 develops the hypothesis relating the scrutiny of analyst questions with the favorableness of the analyst's view of the firm. Sections 3 and 4 outline the empirical methodology and execute the empirical analysis to establish an association between question scrutiny and the analyst's view of the firm. Section 5 utilizes the results of earlier sections to develop a discrimination proxy and describes potential conflicting effects of discrimination on earnings news. Sections 6 and 7 test for the effects of discrimination on earnings news. Section 8 investigates the regulatory interpretation of discrimination and Section 9 concludes.

3.2 Literature Review and Hypothesis development regarding analyst question scrutiny

SEC and regulator interest in managerial discrimination during earnings conference calls ultimately stems from the concern that discrimination could lead investors to rely on positively biased analyst research (Cox 2005). As discussed in Chapter 2, discrimination imposes additional information search costs on unfavorable analysts following the firm. Such an increase in information search costs either forces the unfavorable analyst to drop coverage or upgrade his/her view of the firm in order to gain access to key company information. Either situation results in positively biased analyst views of the company persisting in the marketplace upon which an investor, particularly an unsophisticated investor, may rely.

The aforementioned scenario implies a sequence of events. Managers first discriminate, then analysts drop coverage or upgrade their recommendation, and finally investment decisions are made based on the prevailing analyst view of the stock. However, this scenario ignores the potential real time implications of discrimination with respect to the interpretation of earnings news. Discrimination by definition means that the manager will discuss firm prospects with, and answer questions from, the more favorable analysts following the firm. If a relatively favorable analyst asks less scrutinizing questions of the manager than a relatively unfavorable analyst would, the conference call dialog may paint the firm in a more favorable light and allow the manager to highlight more favorable aspects of the firm. Put another way, discrimination during earnings conference calls may allow the manager to discuss earnings in a “friendly” environment. This could lead some investors to believe that good (bad) news earnings is better than (not as bad as) it actually is.

Zuckerman (2005) provides an example of such a situation. In a June 2005 monthly sales press release, executives at Abercrombie & Fitch provided information about substantial increases in denim sales volume in response to analyst concerns raised during its second quarter conference call about denim growth. However, the executives failed to provide information that this sales growth was accompanied by lower margins. At the earnings release date, both actual sales growth and the related margins were unveiled, leading investors to question why the company had earlier provided good news about sales growth without the accompanying bad news about margin deterioration. The company responded that Wall Street did not ask specifically about denim margins but rather only about denim growth.

As this anecdote shows, if managers know that certain types of analysts will ask questions that ultimately lead to highlighting the positive aspects of the firm, dealing with those analysts during the conference call can help portray the firm in a more favorable light. Of course, a necessary condition for such a managerial strategy is that favorable (unfavorable) analysts ask less (more) scrutinizing questions. I define a scrutinizing question to be one that critically inspects the prospects and risks of the firm, while considering the manager's predisposition to highlight (downplay) positive (negative) aspects of the firm.[23] More scrutinizing questions should therefore be direct, tough, challenging, and tend to result in less positive managerial responses than less scrutinizing questions.

Prior research provides little evidence on the scrutinizing nature of questions analysts ask of managers during earnings conference calls. Tasker (1998a) investigates the questions asked by analysts following twelve technology companies in 1997 and shows that the questions tend to relate to items not addressed in the financial statements. Francis et al. (1997) investigate the questions analysts pose to 200 corporations presenting at the New York Society of Security Analyst meetings. They show that analysts ask questions about historical accounting information and future prospects. Additionally, they code whether analyst questions were aggressive or passive and whether the manager's answer was positive, neutral or negative, but do not incorporate these data into their analysis.

[23] This assumption about manager predisposition is supported by both the literature and the conservative nature of Generally Accepted Accounting Principles. The accounting literature provides empirical examples of firms highlighting the most favorable aspects of their performance through framing (Schrand and Walther 2000) and accounting method choice (Bowen et al. 1995). GAAP's conservative principles governing the recording of assets and liabilities are grounded in the notion that managers, if given the opportunity, would tend to overstate (understate) assets and income (liabilities and expense).

Ultimately neither study explores whether question type varies with the analyst's existing view of the firm.

Whether the scrutiny of analyst questions would vary with their existing views of the firm is unclear and ultimately an empirical question. On one hand, analysts have incentives to continually uncover new information about the firms they follow in order to provide valuable insights for their investor clients. This implies that analysts would ask scrutinizing questions regardless of any existing stock recommendation they have outstanding on the firm.

On the other hand, favorable analysts may face pressures from both managers and certain investor clients that would prevent them from asking scrutinizing questions. If an analyst obtained access to the conference call because of a favorable outstanding stock recommendation as documented in Chapter 2, it is unlikely the analyst would publicly scrutinize the manager during the conference call and jeopardize future conference call access. Additionally, the favorable analyst may have investor clients that have taken long positions based on the existing favorable recommendation. These investors may threaten to withdraw lucrative trade commission-generating business from the analyst's brokerage house if the analyst uncovers negative news about the firm (Morgenson 2006).

Finally, question scrutiny may vary with the favorableness of the analyst's view due to cognitive biases. Aside from economic incentives, analysts may suffer from confirmation bias. Confirmation bias suggests individuals will seek information consistent with their own priors (Arkes 1991). Koonce and Mercer (2005) provide an example of such a situation, where analysts with *ex ante* strong buy recommendations on a stock subconsciously seek information supporting the strong buy recommendation, in spite of their incentives to provide the most accurate recommendation. In the conference call setting, Montier (2005) notes that rather than asking probing questions that look to disconfirm their existing view, favorable analysts end up asking leading questions that support the outstanding stock recommendation.

In summary, analysts are pulled in many directions. Incentives to obtain new information about the firm which should result in no association between their existing recommendation and the scrutiny of the questions they ask. Incentives to maintain managerial and client relations, coupled with confirmation bias, suggests that more favorable (unfavorable) analysts will ask less (more) scrutinizing questions. Combined, the net effect of these incentives should yield an inverse relation between question scrutiny and the favorableness of the analyst's outstanding view of the firm:

H4: The scrutiny of an analyst's question is decreasing in the favorableness of the analyst's view of the firm.

Graham et al. (2005) provide survey evidence suggesting that managers believe analysts become more scrutinizing when the company misses quarterly earnings targets. The authors note that when companies "…meet the earnings target, they can devote the conference call to the positive aspects of the firm's future prospects…if the company fails to meet the guided number, the tone of the conference call becomes negative…analysts begin to doubt the credibility of the assumptions underlying the current earnings number and the forecast of future earnings." To my knowledge, this survey evidence has not been explored empirically.

If these managerial survey claims are true, when a firm misses earnings, favorable analysts should become more scrutinizing.[24] This should dampen the relation hypothesized in H4. In the extreme, favorable analysts may become as scrutinizing as unfavorable analysts, implying that stock recommendations will not be associated with question scrutiny among firms that miss earnings targets. Stated formally:

> *H4a: The inverse relation between the scrutiny of an analyst's question and the favorableness of the analyst's view of the firm will be stronger for firms that meet or beat earnings targets compared with firms that miss earnings targets.*

3.3 Sample selection, research design and variable measurement

Sample

The empirical analysis begins by isolating the 55,862 analyst-firm-quarter observations from Chapter 2 where the analyst participated on the conference call by asking a question. I then retain only those observations where the firm's average outstanding consensus recommendation is between 2.8 and 3.2.[25] Doing so reduces the sample size to 8,785 observations and helps ensure two things. First, the consensus *ex ante* view of the firm is relatively constant within the sample, which removes the potential for question scrutiny to be associated with consensus market views of the firm. Second, variation around this particular "hold" consensus recommendation level should result in individual analyst observations that span the spectrum from strong sell to strong buy.

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[24] Of course, the claim in Graham et al. (2005) that "analysts become more scrutinizing when a firm misses earnings" could also be evidenced by both favorable and unfavorable analysts increasing their scrutiny levels. This would represent a mean scrutiny shift in *all* analysts when a firm misses earnings and would preserve the scrutiny difference between favorable and unfavorable analysts. This interpretation would work against finding results in support of H4a. I allow for this potential interpretation in the empirical specification by including an indicator variable for firms that miss earnings targets.

[25] Individual analyst recommendations are on a 5 point scale, where 1 equals strong buy, 3 equals hold, and 5 equals strong buy. Thus, these firms have average recommendations tightly bound around the hold.

I then randomly select 25 analyst-firm-quarter observations from each of the five stock recommendation levels for analysis, yielding 125 manager-analyst conference call dialogs. Each individual manager-analyst dialog includes both the question(s) posed by the analyst and the response from the manager to the question. A random selection of manager-analyst dialogs from the set of 8,785 is required due to the labor intensive exercise of reading and coding scrutiny aspects for each manager-analyst dialog. The average manager-analyst dialog in the random sample is 678 words. At 250 words per page this random sample alone approaches 340 pages of double-spaced, twelve point font text.

The 125 manager-analyst dialogs were then assigned equally across eighteen different PhD student coders. Coders had no knowledge of the outstanding stock recommendation of the analyst in the manager-analyst dialog they reviewed. Coders were asked to read their assigned manager-analyst dialog and provide Likert scale responses from 1 to 9 on various dimensions of scrutiny. As mentioned previously, scrutinizing questions should be characterized by questions that are direct, tough, and challenging. Scrutinizing questions, compared with non-scrutinizing questions, should result in less positive information being discussed by the firm in answer to the analyst's question.

Variable definitions for each of the following Likert based variables (*SCRUTINIZING, OPENENDED, TOUGH, CHALLENGING,* and *NEGNEWS*), including the questions that induce the Likert scale response, are provided in Appendix 2. Because of the subjective nature inherent in coding scrutiny aspects, linguistic software was also utilized to measure the level of positivity in the manager-analyst dialog. The use of linguistic software trades off subjectivity benefits with costs associated with the inability to account for contextual meaning across words. The General Inquirer (GI) linguistic software was utilized and a detailed discussion of GI is presented in Appendix 3.

Each of the 125 manager-analyst dialogs were read by GI to calculate the number of positive and negative words in the dialog. The positivity measure, *NETPOS_GI*, was constructed consistent with Davis et al. (2006) as the difference between the number of positive words and the number of negative words, scaled by the total number of words in the manager-analyst dialog. This measure represents the percentage of the dialog that contained net positive language, and can vary from between -1 and +1. Larger positive (negative) values indicate more positive (negative) manager-analyst dialog.

Research design and variable measurement for testing H4 and H4a

To test for a relationship between the scrutiny of the analyst's question and the favorableness of the analyst's view of the firm, I estimate the following OLS regression separately for each of the six scrutiny proxies previously defined:

$$SCRUTINY\_PROXY^{i} = \beta_0^i + \beta_1^i \mathrm{Re}c + \beta_2^i Miss + \beta_3^i(\mathrm{Re}c \times Miss) + \upsilon^i \qquad (4)$$

where *SCRUTINY_PROXY*$^i \in$ *(SCRUTINIZING, OPENENDED, TOUGH, CHALLENGING, NEGNEWS, NETPOS_GI)*, and other regression variables are defined in Appendix 2.

I use the existing outstanding stock recommendation (*Rec*) of the analyst immediately prior to the earnings conference call as a proxy for the analyst's view of the firm, consistent with Chapter 2. H4 predicts that an inverse relationship will exist between the scrutiny of the analyst's questions of management and the favorableness of the analysts view. As such, I expect questions that are more scrutinizing, less open-ended, tougher, more challenging, and lead to relatively more negative information about the firm to be associated with less favorable stock recommendations. Empirically, this implies

$\beta_1^{SCRUTINIZING}$, β_1^{TOUGH}, $\beta_1^{CHALLENGING}$ and $\beta_1^{NEGNEWS}$ < 0, as well as $\beta_1^{OPENENDED}$ and $\beta_1^{NETPOS\_GI}$ > 0.

H4a posits that the inverse relation between question scrutiny and the favorableness of the analyst's view will be moderated by the sign of the earnings surprise. More specifically, the relationship between *SCRUTINY_PROXY* and *Rec* will be less pronounced when the firm misses the earnings target. Evidence supporting this hypothesis would include $\beta_3^{SCRUTINIZING}$, β_3^{TOUGH}, $\beta_3^{CHALLENGING}$ and $\beta_3^{NEGNEWS}$ > 0, as well as $\beta_3^{OPENENDED}$, and $\beta_3^{NETPOS\_GI}$ < 0.

3.4 Results for H4 and H4a

Table 11 provides regression variable descriptive statistics for the random sample of 125 manager-analyst dialogs. By construction, the mean individual outstanding recommendation (*Rec*) is 3, consistent with the sample having equal proportions of strong buy, buy, hold, sell and strong sell recommendations. Each of the manually coded scrutiny proxies (*SCRUTINIZING, OPENENDED, TOUGH*, *CHALLENGING*, *NEGNEWS*), which take on values between 1 and 9, show a moderate level of variation. For example, *SCRUTINIZING* has an inter-quartile range of 3 and a standard deviation of 2.262 about a mean of 4.576. So, despite the small sample size, the variation in these measures should help improve the power of the tests.

The variable generated by the linguistic software, *NETPOS_GI*, has a mean of 2.9%. Values greater than zero imply that the dialog generated more positive words than negative words. Most values of *NETPOS_GI* are greater than zero, suggesting that rarely does the dialog reveal more negative words than positive words. This may not be surprising given that managers retain control over how a question is answered. Despite the fact that these variables primarily range in the greater than zero domain, *NETPOS_GI* exhibits reasonable variation.

Table 12 displays the correlations between the regression variables. The correlations among the various scrutiny proxies suggest they are capturing a common construct, as intended. Statistically significant spearman correlations show that more scrutinizing calls are less open-ended, tougher, more challenging, and lead to more negative dialogs between the manager and analyst. Unreported factor analysis across all of the scrutiny proxies reveals one eigenvalue greater than 1, suggesting the collection of variables captures one latent factor, which I name scrutiny.

Turning to the relation between the analyst's view of the firm and these various scrutiny proxies, spearman rank correlations show that unfavorable recommendations are associated with more scrutinizing questions (ρ (*Rec,SCRUTINIZING*)=-0.217, p = 0.015), tougher questions (ρ (*Rec,TOUGH*)=-0.161, p = 0.073), more challenging questions (ρ (*Rec,CHALLENGING*)=-0.153, p = 0.089) and more negative dialog between the manager and analyst ((ρ (*Rec,NETPOS_GI*)=0.236, p = 0.008). These correlations are consistent with H4. The correlations between *Rec* and *OPENENDED*, and *Rec* and *NEGNEWS* are of the predicted sign but not significant at conventional levels.

The multiple regression results in Table 13 provide further support for H4. In each regression the association between *Rec* and *SCRUTINY_PROXY* is statistically significant in the predicted direction. In particular, more favorable recommendations are associated with less scrutinizing ($\beta_1^{SCRUTINIZING}$ = -0.488, p < 0.001), more open-ended ($\beta_1^{OPENENDED}$ = 0.238, p < 0.084), easier (β_1^{TOUGH} = -0.487, p < 0.001) and less challenging questions ($\beta_1^{CHALLENGING}$ = -0.479, p < 0.001). Favorable recommendations are also associated with less negative ($\beta_1^{NEGNEWS}$ = -0.206, p = 0.031) and more positive ($\beta_1^{NETPOS\_GI}$ = 0.003, p < 0.001) news about the firm.

As a group, the regressions exhibit moderate fit, with adjusted R^2 values that range from 1.86% to 14.60%. Unreported regression results that include additional control variables are individually insignificant, do not improve any model's fit nor impact the inferences drawn on *Rec*. Control variables considered were proxies for the firm's information environment (market to book ratios and the range in analyst quarterly earnings forecasts) in the event that analysts are more optimistic about a firm's prospects in poor information environments (Tse and Yan 2005). Additionally, results from Chapter 2 show that more favorable analysts are higher in the question queue than other analysts. Queue position was therefore added as a control variable to control for the potential for initial questions of managers tend to be less scrutinizing than later questions during the conference call.

Turning to tests of H4a, Table 13 shows that the interaction between *Rec* and *Miss* is in the predicted direction in all six of the regressions, and statistically so in five of them. In particular, $\beta_3^{SCRUTINIZING}$ = 0.446 (p = 0.063), β_3^{TOUGH} = 0.665 (p < 0.001), $\beta_3^{CHALLENGING}$ = 0.581 (p = 0.014), $\beta_3^{NEGNEWS}$ = 0.341 (p = 0.072) and $\beta_3^{NETPOS\_GI}$ = -0.003 (p = 0.036), which implies that the association between analyst scrutiny and the favorableness of the analyst's view of the firm is not as strong when the firm misses earnings targets. In fact, F-tests reveal that when the firm misses earnings, the relationship between *Rec* and the scrutiny proxies statistically disappears.

Put another way, more favorable analysts will be less scrutinizing only in situations where the firm meets or beats earnings. When the firm misses earnings, even the favorable analysts become scrutinizing, and they become as scrutinizing as the unfavorable analysts. This result represents the first empirical evidence to support the survey results of Graham et al. (2005) claiming that the tone of conference calls becomes negative when the firm misses earnings targets.[26]

In unreported analysis, I utilize the one latent scrutiny factor identified in factor analysis as dependent variables in equation (4). The results are consistent with those presented in Table 13. In particular, the latent scrutiny factor is inversely associated the favorableness of the analyst's outstanding stock recommendation. Additionally, when the firm misses earnings, there is no association between the latent scrutiny factor and the analyst's outstanding stock recommendation.

To summarize, the collective results of this section suggest that manager's discrimination choices at the individual analyst level can impact the scrutiny they face during the conference call. Managers will be scrutinized less and be able to highlight the positive aspects of the firm more when they interact with favorable analysts as opposed to unfavorable analysts. However, this phenomenon is asymmetric in the sign of earnings news. For firms missing earnings targets, even the favorable analysts become scrutinizing.

3.5 Interpretation of Earnings News in the Presence of Discrimination

Having established in the previous section that discrimination can impact the scrutiny level of the conference call, I now turn to the potential effects of discrimination on the interpretation of earnings news. Earnings conference calls are designed to assist the market in understanding the implications of current earnings news for the company's

[26] When I regress each scrutiny proxy on only an indicator variable for a firm missing earnings targets, I find that firms missing earnings encounter a statistically higher mean level of scrutiny. Results from estimating equation (4) show that this average result stems from favorable analyst scrutiny becoming more like the unfavorable analyst as opposed to a mean shift in the scrutiny of all analysts.

future prospects (Francis et al. 1997, Frankel et al. 1999, Tasker 1998b, Kimbrough 2005). However it is not clear how discrimination might moderate the market's interpretation of earnings news. Three competing views exist on this issue.

First, regulators are concerned that discrimination could assist a manager in highlighting (downplaying) positive (negative) aspects of the firm (Cox 2005). In the context of interpreting earnings news, regulator concerns would be evidenced by the market incorrectly reacting more positively (less negatively) to good (bad) earnings news in the presence of discrimination than in the absence of discrimination. This scenario requires the assumption that the marginal investor cannot discern that managerial and analyst incentives may be aligned (Malmendier and Shanthikumar, 2004; Mikhail et al. 2005) or the understanding that analysts might suffer from confirmation bias.

An opposing second view argues that investors are sufficiently rational and understand the incentives of managers and analysts, and/or cognitive biases analysts might suffer from. In such a case, investors identify discrimination when it occurs and the standard lemons problem results (Akerlof, 1970). Investors view conference calls where managers discriminate as cheap talk settings, and discount the positive news management provides. Morgenson (2005) highlights this point to investors: "Indeed, retaliation by a company against a straight-talking analyst should be viewed as a red-flag warning that the company or its executives may have something to hide." If one views analyst scrutiny as a cost, only firms with truly high quality earnings news (i.e. good news that is permanent and bad news that is transitory) can afford to incur it. Therefore managers can signal the quality of their earnings news by not discriminating and dealing with the most unfavorable analysts during the conference call (Spence 1973). Lowengard (2006) makes this precise point by mentioning that managers who disagree with an unfavorable analyst should communicate more so with that analyst to prove the analyst view is unwarranted. If this situation holds, then managers who do *not* discriminate should have stronger positive (less negative) market reactions to good and bad earnings news.

A third view comes from managers who make the discrimination choices. Some managers may feel that unfavorable analyst views cannot be changed, despite their best efforts (Lowengard 2006). In such a case, further dialog with the analyst during the earnings conference call uses up time that could be better spent answering questions of other analysts. Additionally, if investors rationally discount any positive claims of managers during the conference call, managers may feel that discriminating helps give them more "air time" to further clarify their positive claims and thereby resolve uncertainty. If this scenario is true, good (bad) earnings news accompanied by discrimination will actually help investors understand positive aspects of the firm that accompany the earnings surprise, and result in a more positive (less negative) earnings response to good (bad) news.[27]

Whether the regulator scenario, the signaling scenario, or the manager scenario dominates on average is unclear *ex ante*. As a result, I posit the following null hypothesis:

H5: The market reaction to earnings is not moderated by the discrimination level of the conference call.

3.6 Sample selection, variable measurement and research design

Sample Selection

[27] A positive firm aspect in the presence of good (bad) news would be information explaining the permanent (transitory) nature of good (bad) earnings news.

I begin with an initial sample of 17,334 conference calls where at least one I/B/E/S analyst participated on the conference call by asking a question. I then eliminate 178 firm-quarter observations due to missing announcement period returns, market value of equity or market to book ratios. I also eliminate 3,968 firm-quarter observations for which expected earnings is unavailable. Unexpected earnings, as discussed in Appendix 2, measures expected earnings as the mean forecast of all analysts issuing earnings estimates within the sixty day window prior to the conference call. Using such a strict criteria for expected earnings trades off losing observations for a more precise measure of expected earnings. Since the focus of this section is the market reaction to earnings news, a sharp expected earnings measure is critical to the analysis. The final sample is 13,188 firm-quarter conference calls.

Variable Measurement - Discrimination

I measure discrimination by examining the difference between the outstanding recommendations held by the analysts that participate on the conference call by asking a question and the outstanding recommendations of all analysts following the firm on I/B/E/S (*Recdiff*). If the average recommendation of the analysts participating on the conference call is more favorable than the population of analysts following the firm (i.e. $Recdiff \geq 0$), I define the call as discriminating. The intuition is that if managers are strategically allowing participation based on the analyst's view of the firm, the participating analysts should have more favorable outstanding stock recommendations.

As discussed in Chapter 2, comparing the analysts that participate to the underlying population of analysts may lead to positive skewness in the *Recdiff* measure. This can occur if some unfavorable analysts in the population of analysts do not seek to participate on the conference call (Hayes 1998). Thus the unobservable population of analysts that attempt to participate on the conference call may be actually more favorable than measured by *Recdiff*. Empirically, this measurement error would incorrectly classify some conference calls as discriminating when in fact they are not. This should add noise to the discrimination partition and lower the power of the tests.

If *Recdiff* is capturing the notion of discrimination, then discriminating calls (i.e. $Recdiff \geq 0$) should, on average, yield less scrutinizing dialog between the manager and analysts. Coding costs prohibit the manual assessment the scrutiny faced by the manager during the entire question and answer dialog. However, the GI linguistic software can be used to provide some evidence on whether *Recdiff* is capturing notions of scrutiny and add construct validity to *Recdiff*.

To provide such evidence, I first run the entire conference call question and answer dialog through GI and measure the number of positive and negative words for the entire conference call question and answer session. I then construct *NETPOS_GItran*, which is calculated exactly as *NETPOS_GI* in the previous section, except now it is measured over the entire conference call question and answer session as opposed to the dialog between the manager and one analyst. As with *NETPOS_GI*, more positive values of *NETPOS_GItran* proxies for less scrutinizing interaction the manager and analysts. If discriminating managers face less scrutiny, then a positive relationship should exist between *Recdiff* and *NETPOS_GItran*. The Spearman correlation between *Recdiff* and *NETPOS_GItran* is 0.017 (p = .024), consistent with discrimination decreasing the scrutiny faced by the manager.[28]

[28] This positive univariate relationship is robust to controlling for the earnings news and the outstanding consensus stock recommendation. I run the following rank regression of $NETPOS\_GItran_{i,j,t} \;=\; \beta_0 + \beta_1$

Research Design and additional variable measurement

To investigate how discrimination might moderate the market reaction to earnings news, I estimate the following pooled cross-sectional Newey-West robust OLS regression:

$$
\begin{aligned}
CAR_{i,j,t} = {} & \beta_0 + \beta_1\, GNNDLarge\_UE_{i,j,t} + \beta_2\, GNDCLarge\_UE_{i,j,t} + \beta_3 GNNDSmall\_UE_{i,j,t} \\
& + \beta_4\, GNDCSmall\_UE_{i,j,t} + \beta_5\, BNNDLarge\_UE_{i,j,t} + \beta_6\, BNDCLarge\_UE_{i,j,t} \\
& + \beta_7\, BNNDSmall\_UE_{i,j,t} + \beta_8\, BNDCSmall\_UE_{i,j,t} + \beta_9\, LNMVE_{i,j,t} \\
& + \beta_{10}\, BOOKMKT_{i,j,t} + \beta_{11}\, RETVOLi,j,t + \upsilon_{i,j,t}
\end{aligned}
\qquad \textbf{(5)}
$$

Appendix 2 describes the exact method for calculating each variable in this equation. The dependent variable, *CAR*, is the cumulative abnormal return during the three day earnings announcement window. The dependent variables of interest, *GNNDLarge_UE, GNDCLarge_UE, GNNDSmall_UE, GNDCSmall_UE, BNNDLarge_UE, BNDCLarge_UE*, *BNNDSmall_UE*, and *BNDCSmall_UE*, represent earnings news in the presence or absence of discrimination for earnings partitioned on both the sign and magnitude of earnings news.

I allow earnings response coefficients (ERCs) to vary by the sign of earnings for two reasons. First, as documented previously, analyst scrutiny varies with the sign of earnings news. When firms miss earnings even favorable analysts become scrutinizing, which suggests that conference calls classified as discriminating may be no different than conference calls classified as non-discriminating. Second, some prior research documents that ERCs are asymmetric with the sign of earnings, with positive surprises having larger ERCs than negative surprises (Basu 1997, Defond and Park 2001).

$UE_{i,j,t} + \beta_2\, Marketrec_{i,j,t} + \beta_3\, Recdiff_{i,j,t} + \varepsilon_t$, where variables are defined in the Appendix 2 and each variable is transformed into its decile rank. If more positive earnings news, more favorable outstanding views of the firm, and discrimination each yield more positive (less scrutinizing) dialog during the question and answer session then $\beta_1>0$, $\beta_2<0$, and $\beta_3>0$. Estimation of this regression yields β_0=4.280 (p<.001), β_1=0.102 (p<.001), β_2=-0.065 (p<.001), and β_3=0.012 (p=0.079).

I also allow the earnings response to vary by the magnitude of the earnings surprise for two reasons. First, Freeman and Tse (1992) document a non-linearity in the returns-earnings relation that suggests large magnitude earnings surprises tend to be viewed by the market as less permanent than small magnitude surprises. I define earnings surprises as large when the absolute value of the earnings surprise scaled by market value is greater than .005 (Freeman and Tse 1992). Second, the implications of large earnings surprises for firm value tend to be the most misunderstood by the market, as evidenced by post earnings announcement drift at both short (Bernard and Thomas 1990, Abarbanell and Bernard 1992) and long (Doyle et al. 2005) time horizons. If managers use discrimination to help them better explain the implications of their earnings news, large earnings surprises should represent a powerful setting to examine the impact of discrimination.

To investigate the effects of discrimination on earnings with these varying characteristics, I compare the coefficients on successive pairs of earnings based dependent regression variables in equation (5). For example, to examine the effects of discrimination on large good news earnings, I compare β_1 with β_2. If discrimination has an incremental effect of unduly highlighting or assisting the market in understanding good news implications, then I expect $\beta_2 > \beta_1$. If on the other hand managers that do not discriminate are incurring scrutiny costs to signal the high quality of their earnings news, I expect $\beta_1 > \beta_2$. A similar analysis is performed for assessing the impact of discrimination for small good news earnings surprises. Again, in this setting if managers are highlighting positive aspects of the firm or helping the market understand positive aspects of the firm, then $\beta_4 > \beta_3$. If non-discrimination is a signal then I expect $\beta_3 > \beta_4$.

Turning to negative earnings surprises, I compare β_5 with β_6 and β_7 with $\beta_{8.}$ If discrimination facilitates managers downplaying of large (small) bad news, or helps the manager explain why bad news isn't truly that bad, then β_6 (β_8) should be less than β_5 (β_7). On the other hand, if non-discrimination is a signal that large (small) bad news is not really that indicative of a decrease in the potential cash flows of the firm, then β_5 (β_7) should be less than β_6 (β_8).

Other studies find that the market reaction to earnings news is affected by firm size-related differences in predisclosure information (Atiase 1985, Freeman 1987), and by growth prospects and risk (Collins and Kothari 1989, Easton and Zmijewski 1989), so I include *LNMVE*, *BOOKMKT* and *RETVOL* as control variables.

3.7 Results on the market reaction to earnings news in the presence of discrimination

Main Results

Table 14 provides descriptive statistics on the firm-quarter observations that comprise the sample. Panel A shows that approximately 55% of the sample conference calls are discriminating. Panel B provides further insights of discrimination by the sign of earnings news. Of the 8,836 good earnings news observations, 4,685 (56%) are accompanied by discriminating conference calls. Similarly, 52% (2,062 of 3,948) of bad earnings news are accompanied by discriminating conference calls. Within each partition of earnings news in Panel B, firms holding discriminating (non-discriminating) calls are larger (smaller) and have lower (higher) book-to-market and prior return volatilities. However, the differences in each of these characteristics across any discrimination/earnings news combination are not economically significant.

The multiple regression results are presented in Table 15. The first column of coefficients provides Newey-West robust pooled estimates of the effects of discrimination on the interpretation of earnings news. Consistent with prior research, and as expected, the coefficients on the eight partitions of earnings (coefficients β_1 through β_8 are positive and statistically significant). Additionally, consistent with Freeman and Tse (1992) large magnitude surprises (β_1, β_2, β_5, β_6) have lower ERCs than small magnitude surprises (β_3, β_4, β_7, β_8).

Turning to the comparisons of interest with respect to discrimination, results show a statistically larger positive earnings response for discrimination in the case of large good news earnings (β_1=1.613 < β_2=2.765, p = 0.01). In terms of economic significance, a firm with large magnitude good news that discriminates receives an earnings multiple more than double that of a firm that does not discriminate. Firms that discriminate with small good news earnings receive an earnings multiple of 9.388, compared with non-discriminating firms who receive a multiple of 8.960. However, this difference is not statistically significant (p= 0.65).

Tests examining of the set of bad news earnings surprises fail to strongly reject the null hypothesis of no discrimination effects for both large and small magnitude earnings surprises. In particular, the ERCs do not statistically differ based on discrimination for large magnitude bad news firms (β_5 vs. β_6, p=0.23). For small magnitude bad news firms, the coefficient difference between β_7 and β_8 is marginally significant with a p value of 0.10. Together these results imply that, compared to the good news earnings situation where discrimination had some positive pricing effects, managers discriminating in the presence of any magnitude bad news receive no softening of the negative market reaction to the earnings news.

The asymmetric effects of discrimination corroborates the earlier results suggesting that, in the presence of an earnings disappointment, the favorable analysts become as scrutinizing as the unfavorable analysts. If both favorable and unfavorable analysts become equally scrutinizing in the presence of bad news, discrimination should no longer represent a meaningful choice variable for a manager wishing to control the scrutiny level he faces. Additionally, the incremental positive market reaction to some good news surprises is consistent with both the possibility that the manager is overselling good news implications to the market and the possibility that the manager is using discrimination to better elaborate on the positive aspects of the firm. These competing hypotheses are investigated below, after robustness tests are performed to assess the stability of the results presented thus far.

Robustness Checks

The second column of coefficients in Table 15 uses the Fama MacBeth (1973) procedure to estimate model (5). Results using this approach show that the average coefficient for discriminating large magnitude good news earnings (3.140) is larger than non-discriminating large magnitude good news earnings (2.150). The difference between coefficients is 0.990, which is similar to the 1.152 difference obtained in the pooled results. Unlike the pooled results, however, this coefficient difference of 0.990 is only statistically significant in a one tailed test at marginally the 10% level (p=0.19 in a two tailed test, 0.095 in a one tailed test). Thus, results are weakly consistent with the pooled estimation with respect to large magnitude good news earnings.

This weak result may be due to low power within each of the 12 quarterly regressions. In the pooled sample, large magnitude good news observations represents 977 of the total sample observations of 13,188 (or approximately 8%). Averaging 977 observations across 12 regressions yields approximately 81 quarterly observations that must be split between discriminating and non-discriminating.

Results using the Fama MacBeth procedure remain consistent for small magnitude good news earnings and large magnitude bad news earnings. As in the pooled results, there appears to be no difference in the discriminating and non-discriminating cases. However, results under Fama MacBeth show that discriminating small magnitude bad news firms have lower average ERC multiples (difference = -2.669, FM t-statistic = -2.44, p=0.03). In particular, such firms that discriminate have an average ERC 7.161, compared with a multiple of 9.830 for firms that do not discriminate. These magnitudes were similar to the 7.595 and 9.719 provided in the pooled results, however their difference there was marginally significant at the 10% level. Thus, at least using this specification, it appears that discriminating helps soften the negative market reaction the firm has to small negative earnings news.

Table 16 assesses the sensitivity of the pooled results for changes in the measurement of the dependent variable. The first (second) column measures abnormal market returns by subtracting the equal weighted CRSP return (size decile return) from the firm's raw return. The coefficients in each regression are similar in magnitude to those reported in Table 15. Discrimination increases the positive market reaction to large good news earnings when the dependent variable is measured using equally weighted CRSP CARs ($\beta_1 < \beta_2$, p = 0.02) or size adjusted CARs ($\beta_1 < \beta_2$, p = 0.02). The coefficient differences for small magnitude good news and large magnitude bad news in discriminating and non-discriminating cases are not statistically significant as in Table 15. Additionally, using the equal weighted CRSP returns adjustment (size decile returns adjustment) provide no statistical support for a discrimination effect in the small magnitude bad news earnings setting (p=0.16 and 0.16, respectively). This results counters the marginal (strong) statistical significance found in this partition in Table 15 under the pooled (Fama MacBeth) approach.

3.8 Implications

As a whole, the evidence thus far is most consistent with managerial discrimination having positive pricing effects for large magnitude good news earnings. This result is consistent with both the regulator scenario and the manager scenario. Regulators are concerned with the positive pricing effects being evidence of unsophisticated investors being fooled into over-reacting. Managers would argue that they are simply removing asymmetry that is otherwise attached to their good news claims. I attempt to distinguish between these competing views by first reassessing the incremental pricing results in the relative presence and absence of sophisticated investors, and then by investigating subsequent stock returns.

Investor Sophistication

The first set of tests relies on the underpinnings of the regulator argument for discrimination yielding overreaction to positive earnings news. Recall that SEC and regulator interest in the potential detrimental effects of discrimination is the protection of the unsophisticated investor. For discrimination to mislead investors, it must be the case that the marginal investor is not aware of the incentive alignment between managers and favorable analysts. If the results documented thus far are consistent with the regulator scenario, then the positive incremental market response to good news in the presence of discrimination should be more pronounced when the marginal investor is relatively unsophisticated.

To consider this case, I re-estimate model (5) while allowing all coefficients to vary with whether the marginal investor is of high or low sophistication:

$$\begin{aligned} CAR_{i,j,t} = \; & HighSoph \times (\beta_0 + \beta_1 GNNDLarge\_UE_{i,j,t} + \beta_2 GNDCLarge\_UE_{i,j,t} + \beta_3 GNNDSmall\_UE_{i,j,t} \\ & + \beta_4 GNDCSmall\_UE_{i,j,t} + \beta_5 BNNDLarge\_UE_{i,j,t} + \beta_6 BNDCLarge\_UE_{i,j,t} \\ & + \beta_7 BNNDSmall\_UE_{i,j,t} + \beta_8 BNDCSmall\_UE_{i,j,t} + \beta_9 LNMVE_{i,j,t} \\ & + \beta_{10} BOOKMKT_{i,j,t} + \beta_{11} RETVOL_{i,j,t}) + \\ & LowSoph \times (\alpha_0 + \alpha_1 GNNDLarge\_UE_{i,j,t} + \alpha_2 GNDCLarge\_UE_{i,j,t} + \alpha_3 GNNDSmall\_UE_{i,j,t} \\ & + \alpha_4 GNDCSmall\_UE_{i,j,t} + \alpha_5 BNNDLarge\_UE_{i,j,t} + \alpha_6 BNDCLarge\_UE_{i,j,t} \\ & + \alpha_7 BNNDSmall\_UE_{i,j,t} + \alpha_8 BNDCSmall\_UE_{i,j,t} + \alpha_9 LNMVE_{i,j,t} \\ & + \alpha_{10} BOOKMKT_{i,j,t} + \alpha_{11} RETVOL_{i,j,t}) + \upsilon_{i,j,t} \end{aligned} \quad \textbf{(6)}$$

where all variables are as previously defined. I use institutional holdings and analyst following as two variables to proxy for the sophistication of the marginal investor (Schrand and Walther 2000). I measure institutional holdings as the percentage of outstanding shares held at the most recent calendar quarter prior to the fiscal quarter end. Analyst following is simply the number of analysts supplying a quarterly earnings forecast to the I/B/E/S consensus forecast immediately preceding the earnings announcement date.

I begin by ranking the full sample of observations in thirds based institutional holdings. I then code investor sophistication as high (*HighSoph* = 1*)* or low (*LowSoph =* 1) if the firm quarter observation falls in the top (bottom) third. The middle third is eliminated to remove noise from the sophistication partition. The results of estimating equation (6) using the institutional holding proxy are presented in the first two columns of Table 17. As shown in the first column, the coefficient difference for large good news in the discriminating versus non discriminating case is 1.370 (α_1=1.542 < α_2=2.912, p = 0.01) for the low sophistication condition, and 2.236 (β_1=1.064 < β_2=3.300, p = 0.01) for the high sophistication condition. Unreported analysis shows that the low sophistication difference of 1.370 is not statistically different than the high sophistication difference of 2.236 (p=0.42). Theses results imply that the discrimination effect in the large magnitude good news partition does not vary with investor sophistication.

When I repeat the same analysis using analyst following as the proxy for investor sophistication, I obtain similar results. Again, both sophisticated and unsophisticated investors react incrementally positively to large magnitude good news earnings ($\beta_1 < \beta_2$ and $\alpha_1 < \alpha_2$). Further the difference in the incremental market reaction is not statistically different between sophisticated and usophisticated investors (p=0.34). The results under both proxies for sophistication are inconsistent with SEC concerns that the incremental positive reaction to large good news earnings is may be evidence of an unsophisticated investor being taken advantage of by management.

Subsequent Market Returns

Another method to distinguish between the regulator and manager scenarios is to examine *ex post* stock returns. Under the regulator scenario of overreaction, as time passes, investors should realize the true state of the firm and unwind the good news claims of managers. Thus, a portfolio of good news earnings surprises where managers discriminate should exhibit negative *ex post* returns as the true state is revealed, while the portfolio of good news earnings surprise where managers did not discriminate should exhibit no reversal in *ex post* returns.

On the other hand, discrimination may simply allow managers to better resolve uncertainty surrounding good news claims. If so, as time passes, investors will resolve uncertainty surrounding good news claims for the non discriminating conference calls. Combined, this implies that, all else equal, a portfolio of good news earnings surprises in the presence of discrimination should exhibit less positive price drift compared with a portfolio of good news earnings surprises in the absence of discrimination.

Interestingly, the fact that the positive incremental price reaction resulting from discrimination is concentrated in the large good news earnings partition makes it more likely that the manager scenario holds as opposed to the regulator scenario. Doyle et al. (2005) document severe under reaction to large good news earnings surprises over a three year horizon, which implies that an incremental reaction to large good news earnings must be extremely large in order to be evidence of over-reaction.

To investigate these competing hypotheses, Table 18 provides and plots cumulative abnormal stock returns (CARs) for two portfolios of good news earnings surprise firms: those that hold discriminating conference calls and those that do not. CARs are accumulated beginning the second day after the earnings announcement through various 10 day increment horizons, ending 90 days from the earnings announcement. The accumulation period examined ends 90 days after the earnings conference call to avoid cumulating returns associated with the subsequent quarterly earnings announcement for the same firm. While this short window limits the time in which potential reversals could occur, it does lend more credence to statistical inferences, which tend to deteriorate as the time horizon widens (Kothari and Warner 1997).

The plotted CARs in Table 18 show that returns to good news surprises accompanied by non-discriminating conference calls are more positive than discriminating conference calls at all time horizons presented. The difference widens as time passes, and at 90 days past the earnings announcement, CARs for non-discriminating conference calls are 3.3%, compared with 1.8% for discriminating conference calls. While this difference is statistically significant at conventional levels, the economic significance is not overpowering. Nonetheless, the results do help disentangle the competing hypotheses presented previously. Consistent with the manager scenario, good news discriminating (non-discriminating) firms exhibit less (more) drift, suggesting that discrimination may simply allow the manager to better resolve uncertainty of good news claims. There appears to be no evidence of return reversal in the window explored, as the regulator scenario predicts.

Unreported analysis regressing the 90 day window CARs on an indicator for whether the good news earnings conference call was discriminating and standard risk proxies (size, market to book and stock price volatility) is consistent with the inferences drawn from Table 18. As such, risk differences between discriminating and non-discriminating good news earnings conference calls do not explain the differential return patterns.

3.9 Conclusion

I provide initial evidence on one potential consequence of managerial discrimination: the interpretation of earnings news. I find that when managers discriminate, the market reacts more strongly to large magnitude good news announcements. I also show that discrimination has no differential effects on small magnitude good news nor on the interpretation of bad news. Collectively, discrimination appears to have an asymmetric impact on the interpretation of earnings news.

I also provide empirical evidence regarding how discrimination could effect the interpretation of earnings news. By discriminating, managers manipulate the scrutiny they will face from the analysts they interact with during the conference call. I show that the scrutiny of analyst questions is negatively associated with the favorableness of the analyst's view of the firm, but only among firms who meet or beat earnings targets. The asymmetric scrutiny relatively favorable analysts place on firms is consistent with the asymmetric market reactions I document and provides the first direct empirical support for the notion that analyst scrutiny varies depending on the sign of the earning surprise (Graham et al. 2005).

From a regulatory standpoint, the incremental market reaction to good earnings news is consistent with market participants potentially believing reported large magnitude good news earnings are better than they really are. However, further investigation reveals that this incremental reaction to good news earnings in the discrimination setting is not concentrated in the subsample of firms where investors are relatively unsophisticated. On the contrary, the discriminatory effects persist to an equivalent extent for both sophisticated and unsophisticated investors Additionally, investigation of returns subsequent to the conference call suggests that discrimination does not predict a reversal in stock returns, as regulator concerns suggest. Rather, firms with good news earnings that discriminate exhibit less price drift that firms that do not discriminate. As a whole, the positive incremental reaction to good news results is inconsistent with regulator concerns that unsophisticated investors are being fooled, and more consistent with managers resolving asymmetry about good news prospects.

The conclusions of this chapter are subject to a number of limitations. First, I only investigate the effects of discrimination on the interpretation of earnings. Regardless of the scrutiny a manager chooses to face via discrimination, other market mechanisms may limit the ability to place a firm in a favorable light in the conference call setting. For instance, a manager can face litigation for overly inflating the firm's prospects or withholding material negative news. Discrimination may therefore have more powerful effects in other settings such as analyst's choice in selecting firms to cover or with respect to covering analyst's career concerns.

Second, I use stock price changes to assess the impact of discrimination. Because stock prices aggregate beliefs about the firm's prospects, a more powerful assessment of the discrimination effects would be to investigate trading behavior of market participants. Indeed, if discrimination results in one group of investors systematically interpreting earnings news as positive and the other negative, the aggregate trade would not impact price but would impact volume.

Finally, it is difficult to conclude that discrimination causes a differential market reaction. A correlated but omitted factor could drive both a manager's discrimination choice and the market reaction to earnings, although such a factor is not obvious. The results presented here are merely associations and should be interpreted as such.

Despite these limitations, I provide initial evidence suggesting discrimination plays a role in the interpretation of earnings news. What impact discrimination may have on other market participants, or what other strategic disclosure choices might be associated with discrimination, are important issues left for future research.

TABLE 1
Sample Characteristics

Panel A: Distribution of firm-quarters and analyst-firm-quarters by calendar quarter

Calendar Quarter of Fiscal Quarter End	Firm-Quarter Observations	%	Analyst-Firm-Quarter Observations	%
2002-Q1	556	3	3,211	2
2002-Q2	1,133	6	8,570	6
2002-Q3	1,282	7	9,269	6
2002-Q4	1,646	8	14,270	10
2003-Q1	1,323	7	7,264	5
2003-Q2	1,750	9	12,712	9
2003-Q3	1,885	10	13,463	9
2003-Q4	2,046	10	17,157	12
2004-Q1	1,692	9	9,160	6
2004-Q2	2,072	11	16,042	11
2004-Q3	2,075	11	16,135	11
2004-Q4	2,217	11	19,455	13
Total	19,677	100%	146,708	100%

Table 1 (continued)

Panel B: Distribution of firm-quarters and analyst-firm-quarters by industry[a]

Industry	**Firm-Quarter Observations**	**%**	**Analyst-Firm-Quarter Observations**	**%**
Chemicals	460	2	2,852	2
Computers	3,678	19	32,238	22
Extractive	844	4	8,668	6
Financial	2,127	11	18,067	12
Food	369	2	2,531	2
Insurance/RealEstate	356	2	1,176	1
Manf:ElectricalEqpt	791	4	5,426	4
Manf:Instruments	1,181	6	7,362	5
Manf:Machinery	667	3	4,845	3
Manf:Metal	361	2	1,954	1
Manf:Misc.	128	1	801	1
Manf:Rubber/glass/etc	233	1	1,027	1
Manf:TransportEqpt	381	2	2,748	2
Mining/Construction	418	2	2,499	2
Pharmaceuticals	83	0	506	0
Retail:Misc.	1,103	6	7,847	5
Retail:Restaurant	1,231	6	10,251	7
Retail:Wholesale	277	1	2,497	2
Services	470	2	2,556	2
Textiles/Print/Publish	1,852	9	12,916	9
Transportation	847	4	5,165	4
Utilities	1,155	6	9,253	6
Not Assigned	665	3	3,523	2
Total	19,677	100%	146,708	100%

Panel C: Distribution of firm-quarters by stock exchange

Stock exchange	**Firm-Quarter Observations**	**%**
NYSE	10,767	54
NASDAQ	8,608	44
AMEX	142	1
Non AMEX, NYSE, NASDAQ	160	1
Total	19,677	100%

[a] Industry definitions are obtained from Barth et al. (2005).

TABLE 2
Firm level descriptive statistics for 19,677 Conference Call Transcripts

Variable[a]	**N**	**Mean**	**Q1**	**Median**	**Q3**	**Std Dev**
Firm and CEO Characteristics						
Assets – Total ($MM)	19,677	11,409.192	377.295	1,212.513	4,489.444	59,411.654
Market Value of Equity ($MM)	19,482	6,077.712	473.318	1,187.188	3,663.366	20,884.771
Market to Book Ratio	19,476	3.585	1.474	2.183	3.444	73.350
Return on Assets	19,668	0.002	0.001	0.009	0.020	0.060
CEO option wealth sensitivity ($MM)	11,252	0.519	0.070	0.182	0.462	1.604
InstHold	19,677	0.588	0.413	0.657	0.818	0.296
Conference Call Characteristics						
CorpCount	19,677	3.411	3.000	3.000	4.000	1.389
NonCorpCount	19,677	8.799	6.000	9.000	11.000	4.284
NumAnalyst	19,677	7.456	3.000	6.000	10.000	5.840
IBESonCall	19,677	3.859	2.000	3.000	6.000	3.025
IBESonCallDum	19,677	0.881	1.000	1.000	1.000	0.324
Length of Conference Call (min)	19,677	52.381	40.753	52.387	62.893	17.239
Length of Q&A (min)	19,677	29.475	19.687	29.760	39.160	15.310
Open	19,677	0.551	0.472	0.587	0.682	0.204
MarketRec	19,677	2.419	2.067	2.400	2.750	0.499
OnCallRec	17,334	2.324	2.000	2.333	2.800	0.654
MarketEst	19,677	0.273	0.060	0.230	0.440	0.404
OnCallEst	17,334	0.276	0.060	0.230	0.450	0.417
Actual	19,672	0.273	0.050	0.230	0.460	0.470
MarketFE	19,672	0.000	-0.020	0.010	0.030	0.198
OnCallFE	17,331	0.008	-0.010	0.010	0.030	0.191

[a] See Appendix 1 for variable definitions.

TABLE 3
Descriptive and univariate analysis of analyst conference call participation

Panel A:

	Full Sample		*OnCall = 0 (N=90,846)*		*OnCall = 1 (N=55,862)*		**Mean**		**Median**	
Variable[a]	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Difference**		**Difference**	
Analyst View of the firm										
OnCall	0.381	0.000	0.000	0.000	1.000	1.000	N/A		N/A	
Sbuy	0.199	0.000	0.181	0.000	0.227	0.000	-0.046	***	N/A	
Buy	0.264	0.000	0.248	0.000	0.290	0.000	-0.042	***	N/A	
Hold	0.450	0.000	0.475	0.000	0.408	0.000	0.067	***	N/A	
Sell	0.068	0.000	0.074	0.000	0.059	0.000	0.015	***	N/A	
Ssell	0.019	0.000	0.022	0.000	0.016	0.000	0.006	***	N/A	
Time and Competition Constraints										
Open	0.561	0.597	0.531	0.575	0.610	0.625	-0.079	***	-0.051	***
NumAnalyst	12.029	11.000	12.568	11.000	11.153	10.000	1.414	***	1.000	***
Analyst Characteristics										
AllStar	0.177	0.000	0.151	0.000	0.220	0.000	-0.069	***	N/A	
PriorAcc	0.697	0.800	0.688	0.800	0.711	0.819	-0.023	***	-0.019	***
FirmExp_Raw	3.374	2.282	3.270	2.236	3.544	2.416	-0.274	***	-0.181	***
FirmExp	0.462	0.377	0.450	0.357	0.480	0.409	-0.030	***	-0.052	***
GenExp_Raw	7.479	5.847	7.429	5.808	7.562	5.907	-0.133	***	-0.099	***
GenExp	0.386	0.295	0.383	0.291	0.391	0.301	-0.008	***	-0.010	***
Inds_Raw	3.297	3.000	3.252	3.000	3.370	3.000	-0.118	***	0.000	***
Inds	0.389	0.333	0.389	0.333	0.389	0.333	0.000		0.000	
ForFreq_Raw	15.483	13.000	15.282	12.000	15.811	13.000	-0.529	***	-1.000	***
ForFreq	0.423	0.360	0.410	0.343	0.444	0.389	-0.034	***	-0.046	***
BrokerSize_Raw	91.916	60.000	88.207	59.000	97.948	67.000	-9.741	***	-8.000	***
BrokerSize	0.338	0.237	0.326	0.215	0.358	0.274	-0.032	***	-0.059	***
Companies_Raw	15.817	15.000	15.953	15.000	15.598	15.000	0.355	***	0.000	***
Companies	0.472	0.440	0.469	0.435	0.477	0.450	-0.008	***	-0.015	***
OnCallPrior	0.584	1.000	0.446	0.000	0.807	1.000	-0.361	***	N/A	
RecHorizon	297.942	247.000	312.873	269.000	273.662	212.000	39.211	***	57.000	***
Queue|OnCall	N/A	N/A	N/A	N/A	0.501	0.500	N/A		N/A	
Time|OnCall	N/A	N/A	N/A	N/A	2.606	2.253	N/A		N/A	

Table 3 (continued)

Panel B: Pearson (Spearman) Correlations on the Upper (Lower) Diagonal[a,b]

	OnCall	*Que| OnCall*	*Time| OnCall*	*IBES Rec*	*Open*	*Prior Acc*	*All Star*	*Num Analyst*	*Companies*	*Gen Exp*	*Firm Exp*	*For Freq*	*Inds*	*Broker Size*	*OnCall Prior*	*Rec Horizon*
OnCall		N/A	N/A	-0.082	0.190	0.035	0.087	-0.093	0.013	0.013	0.042	0.050	**0.000**	0.049	0.355	-0.080
Que| OnCall	N/A		0.118	-0.057	0.072	**0.004**	0.108	-0.045	0.064	0.021	0.059	**0.006**	0.015	0.128	0.067	**0.005**
Time| OnCall	N/A	0.130		-0.032	0.125	-0.035	**0.007**	-0.202	0.034	0.044	0.070	0.046	0.033	0.062	0.063	0.025
IBESRec	-0.085	-0.061	-0.027		-0.006	0.007	0.088	0.015	0.023	**-0.004**	-0.021	-0.018	-0.022	0.129	-0.012	-0.103
Open	0.170	0.073	0.093	-0.020		0.008	**-0.002**	0.030	0.008	-0.016	-0.019	**-0.002**	-0.004	-0.013	0.111	-0.011
PriorAcc	0.041	**0.005**	-0.013	**0.003**	0.010		0.028	0.129	-0.005	-0.037	-0.030	0.018	-0.010	-0.018	**-0.002**	-0.083
AllStar	0.087	0.109	0.025	0.087	**0.004**	0.019		0.023	0.135	0.165	0.128	-0.038	0.025	0.341	0.081	-0.024
Num Analyst	-0.087	-0.044	-0.197	0.016	0.053	0.055	0.042		-0.060	-0.122	-0.128	-0.072	-0.120	-0.142	-0.051	0.012
Companies	0.015	0.065	0.034	0.021	0.011	0.006	0.136	-0.045		0.333	0.219	0.086	0.423	0.128	0.039	0.040
GenExp	0.014	0.026	0.035	**-0.004**	-0.011	-0.022	0.184	-0.072	0.365		0.469	0.043	0.189	0.109	0.036	0.087
FirmExp	0.041	0.061	0.068	-0.021	-0.020	-0.017	0.130	-0.113	0.229	0.493		0.128	0.122	0.095	0.094	0.120
ForFreq	0.050	**0.004**	0.036	-0.016	**0.001**	0.031	-0.029	-0.035	0.092	0.051	0.148		0.028	-0.051	0.092	**0.004**
Inds	**0.003**	0.018	0.025	-0.024	**0.001**	0.006	0.035	-0.093	0.419	0.195	0.125	0.029		-0.017	0.008	0.025
Broker Size	0.057	0.137	0.061	0.149	-0.008	**-0.001**	0.369	-0.068	0.144	0.114	0.092	-0.031	-0.033		0.065	-0.013
OnCall Prior	0.355	0.065	0.075	-0.014	0.093	**0.003**	0.081	-0.042	0.042	0.049	0.103	0.097	0.012	0.080		0.037
Rec Horizon	-0.092	**0.003**	0.027	-0.084	-0.017	-0.087	-0.030	0.011	0.029	0.069	0.100	0.013	0.019	**0.003**	0.050	

*, **, *** Significant at the 0.10, 0.05 and 0.01 level for t-test of means and wilcoxon test of medians for continuous variables, and chi-square test of equal proportions for indicator variables.

[a] See Appendix 1 for variable definitions.

[b] All correlations are significant at the .10 level or better unless indicated in **bold**.

TABLE 4
Logistic regression investigating the association between conference call participation and the favorableness of the analyst's view of the firm

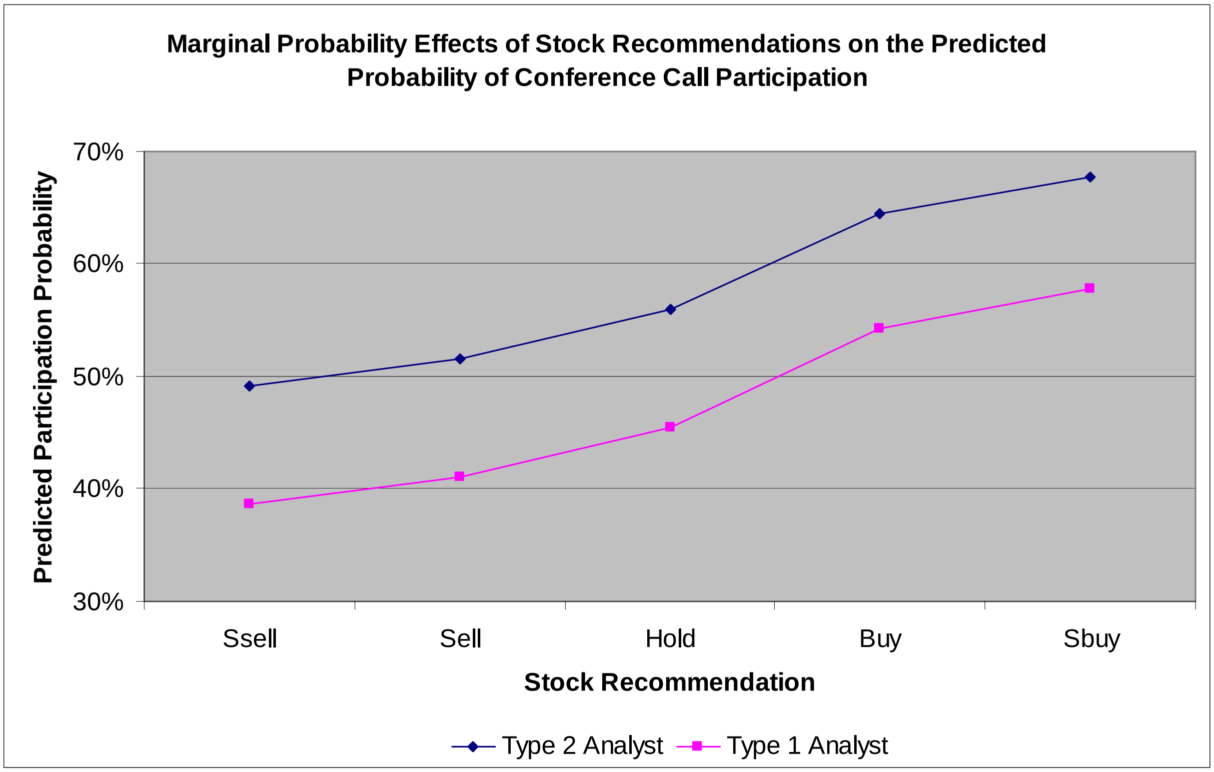
Panel A: Model Estimation

$$OnCall_{i,j,t} = \beta_0 + \beta_1 Sbuy_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4 Ssell_{i,j,tt} + \beta_5 Open_{i,j,t} + \beta_6 NumAnalyst_{i,j,t} + \beta_7 AllStar_{i,j,t} + \beta_8 PriorAcc_{i,j,t} + \beta_9 FirmExp_{i,j,t} + \beta_{10} GenExp_{i,j,t} + \beta_{11} Inds_{i,j,t} + \beta_{12} ForFreq_{i,j,t} + \beta_{13} BrokerSize_{i,j,t} + \beta_{14} Companies_{i,j,t} + \beta_{15} PriorOnCall_{i,j,t} + \beta_{16} RecHorizon_{i,j,t} + \upsilon_{I,j,t} \quad (1)$$

Variable [a]	Predicted Sign	Coefficients		Odds Ratio	χ^2 *statistic*[c]
Intercept	?	-2.569	***		2,464.80
Analyst view of the firm					
Sbuy	+ and > β_2	0.500	***	1.649	564.91
Buy	+	0.356	***	1.428	346.87
Sell	-	-0.174	***	0.840	27.03
Ssell	- and < β_4	-0.274	***	0.760	23.54
Time and Competition Constraints					
Open	+	2.131	***	8.425	1,071.39
NumAnalyst	-	-0.031	***	0.970	394.99
Analyst quality					
AllStar	+	0.423	***	1.527	306.48
PriorAcc	+	0.279	***	1.321	157.18
FirmExp	+	0.071	***	1.074	6.19
GenExp	+	-0.088	***	0.916	9.01
Inds	-	-0.073	***	0.929	8.04
ForFreq	+	0.115	***	1.122	24.42
BrokerSize	+	0.069	***	1.071	6.20
Companies	-	-0.045	*	0.956	2.41
OnCallPrior	+	1.628	***	5.093	7,580.25
RecHorizon	-	-0.001	***	0.999	692.17
Sample Size [b]		146,708			
Pseudo R^2		14.9%			
Percent correctly predicted		70.0%			

Tests	χ^2 *statistic*[c]	*Prob*(χ^2)
Wald goodness-of-fit[d]	10,332	<.001
$\beta_1 = \beta_2$	42.25	<.001
$\beta_3 = \beta_4$	2.42	0.060

Panel B: Marginal Probability Effect Plots [e]



***, **, * Significant at .01, .05 and .10 level, respectively, in two-tailed test (one-tailed when predicted).
[a] See Appendix 1 for variable definitions.
[b] The sample includes 146,708 analyst-firm-quarter observations.
[c] Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with firm level clustering (Rogers 1993) for lack of independence of analyst observations by firm.
[d] Wald goodness of fit test is utilized in place of a likelihood ratio test because of clustered maximum likelihood estimates.

[e] Predicted probabilities are calculated as $e^{(x'\hat{\beta})}/(1+e^{(x'\hat{B})})$, where $\hat{\beta}$ is the vector of fitted values from equation (1) reported in Panel A and x' is the vector of values equal to the sample mean (see Table 2, Panel B) for all continuous variables, and 1 for *PriorOnCall*. Remaining values for stock recommendations and all-star status take on values of 1 or 0 depending on their respective location in the graph.

TABLE 5
Logistic regression investigating the association between conference call participation and the relative favorableness of the analyst's view of the firm

Panel A: Model Estimation

$$OnCall_{i,j,t} = \beta_0 + \beta_1 RelRec + \beta_2 Open_{i,j,t} + \beta_3 NumAnalyst_{i,j,t} + \beta_4 AllStar_{i,j,t} + \beta_5 PriorAcc_{i,j,t} + \beta_6 FirmExp_{i,j,t} + \beta_7 GenExp_{i,j,t} + \beta_8 Inds_{i,j,t} + \beta_9 ForFreq_{i,j,t} + \beta_{10} BrokerSize_{i,j,t} + \beta_{11} Companies_{i,j,t} + \beta_{12} PriorOnCall_{i,j,t} + \beta_{13} RecHorizon_{i,j,t} + \upsilon_{I,j,t}$$

Variable [a]	Predicted Sign	Coefficients		Odds Ratio	χ^2 *statistic*[c]
Intercept	?	-2.624	***		2,464.80
Analyst view of the firm					
RelRec	+	0.460	***	1.585	830.39
Time and Competition Constraints					
Open	+	2.125	***	8.376	3869.34
NumAnalyst	-	-0.031	***	0.969	1228.26
Analyst quality					
AllStar	+	0.426	***	1.531	644.15
PriorAcc	+	0.285	***	1.321	215.91
FirmExp	+	0.089	***	1.093	19.61
GenExp	+	-0.093	***	0.911	17.38
Inds	-	-0.077	***	0.926	15.46
ForFreq	+	0.128	***	1.137	46.22
BrokerSize	+	0.064	***	1.066	9.58
Companies	-	-0.040	*	0.960	3.05
OnCallPrior	+	1.621	***	5.055	8,953.70
RecHorizon	-	-0.001	***	0.999	981.88
Sample Size [b]		141,480			
Pseudo R^2		14.6%			
Percent correctly predicted		75.0%			

Tests	χ^2 *statistic*[c]	***Prob***(χ^2)
Wald goodness-of-fit[d]	11,421	<.001

***, **, * Significant at .01, .05 and .10 level, respectively, in two-tailed test (one-tailed when predicted).
[a] See Appendix 1 for variable definitions.
[b] The initial sample includes 146,708 analyst-firm-quarter observations and 141,480 used in estimation. The loss of observations relative to the initial sample results from observations where there was no dispersion in the analyst forecasts, which results in a zero denominator in the *RelRec* measure.
[c] Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with firm level clustering (Rogers 1993) for lack of independence of analyst observations by firm.

TABLE 6
Logistic regression investigating the association between the probability of conference call participation and changes in stock recommendations

PANEL A:

$$OnCall^{s} = \beta_0^{s} + \sum_{m=1}^{10} \beta_m^{s} Upgrades + \sum_{n=11}^{20} \beta_n^{s} Downgrades + \beta_{21}^{s} NumAnalyst + \beta_{22}^{s} Open + \varepsilon^{s} \quad (1a)$$

where s = the $OnCall_{i,j,t-1}=1$ or the $OnCall_{i,j,t-1}=0$ sample

			Sample: $OnCall_{i,j,t-1} = 1$			***Sample: $OnCall_{i,j,t-1} = 0$***		
Recommendaiton Level Change[b]	**Variable** [a]	**Predicted Sign**	**Coefficients**		**χ^2 *statistic***[c]	**Coefficients**		**χ^2 *statistic***[c]
	Intercept	?	-0.813	***	57.64	-1.400	***	173.75
Upgrades								
1	*Ssell to Sell*	+	N/A[e]		N/A[e]	-0.408		0.60
1	*Sell to Hold*	+	-0.181		1.80	-0.117		0.99
1	*Hold to Buy*	+	0.233	***	5.93	0.134	*	2.50
1	*Buy to Sbuy*	+	0.243	**	3.22	0.116		0.87
2	*Ssell to Hold*	+	-0.137		0.51	-0.562	***	10.75
2	*Sell to Buy*	+	-0.277		0.85	0.098		0.12
2	*Hold to Sbuy*	+	0.218	**	4.59	-0.021		0.05
3	*Ssell to Buy*	+	0.041		0.00	N/A[f]		N/A[f]
3	*Sell to Sbuy*	+	0.169		0.05	-0.564		0.52
4	*Ssell to Sbuy*	+	N/A[e]		N/A[e]	N/A[e]		N/A[e]
Downgrades								
1	*Sbuy to Buy*	-	0.232	**	4.13	0.174	*	2.86
1	*Buy to Hold*	-	-0.012		0.02	-0.168	**	5.06
1	*Hold to Sell*	-	-0.243	**	4.31	-0.315	***	9.53
1	*Sell to Ssell*	-	0.113		0.07	-0.393		1.02
2	*Sbuy to Hold*	-	-0.060		0.41	-0.079		0.84
2	*Buy to Sell*	-	-0.236		0.85	-0.669	***	7.03
2	*Hold to Ssell*	-	-0.152		0.71	-0.028		0.03
3	*Sbuy to Sell*	-	N/A[e]		N/A[e]	-0.973	*	2.18
3	*Buy to Ssell*	-	-1.380		0.89	0.460		0.36
4	*Sbuy to Ssell*	-	0.635		0.89	0.891		2.66
Control Variables								
	NumAnalyst	-	-0.013	***	11.75	-0.033	***	95.41
	Open	+	2.702	***	311.29	1.921	***	161.02
	Sample Size [d]		7,501			9,034		
	Pseudo R^2		5.0%			3.7%		
	Percent correctly predicted		68.9%			68.5%		

PANEL B:

$$OnCall^{s} = \beta_0^s + \beta_1^s \operatorname{Re} cChange + \beta_2^s Numanalyst + \beta_3^s Open + \varepsilon^s \quad (1a)$$

where s = the $OnCall_{i,j,t-1}=1$ or the $OnCall_{i,j,t-1}=0$ sample

	Variable [a]	Predicted Sign	Coefficients		χ^2 statistic[c]	Percent correctly predicted	Pseudo R^2
Sample: $OnCall_{i,j,t-1}$ = 1						60.9%	4.6%
	Intercept	?	-0.769	***	74.72		
	RecChange	+	0.055	***	7.64		
	NumAnalyst	-	-0.013	***	13.07		
	Open	+	2.695	***	400.95		
Sample: $OnCall_{i,j,t-1}$ = 0						62.3%	3.7%
	Intercept	?	-1.452	***	277.17		
	RecChange	+	0.024	*	1.58		
	NumAnalyst	-	-0.033	***	103.89		
	Open	+	1.914	***	226.25		

Notes to Table 6:
*, **, *** Significant at the 0.10, 0.05 and 0.01 level (one tailed for signed predictions).
[A] Upgrades and downgrades are indicator variables for recommendation changes occurring during between consecutive quarterly earnings conference call. See Appendix 1 for variable definitions.
[b] Recommendation level changes represents the magnitude of the upgrade or downgrade as the number of recommendation levels between the prior and current recommendation change.
[c] Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with firm level clustering (Rogers 1993) for lack of independence of analyst observations by firm.
[d] The sample consists of the subset of all analyst-firm-quarter observations where analyst participation was measurable on both the current and prior quarter earnings conference call, and where the analyst made a recommendation change or reiteration between the two conference calls. The $OnCall_{i,j,t-1}=0$ sample examines changes in participation probabilities for those analysts who did not previously participate on the conference call. The $OnCall_{i,j,t-1}=1$ sample examines changes in participation probabilities for those analysts who did previously participate on the conference call.
[e] Represents 17 upgrade and downgrade observations that were not included in the model because the upgrade or downgrade combination predicted participation perfectly.
[f] This upgrade combination does not exist in the sample.

TABLE 7
Fama MacBeth logistic regression investigating the association between conference call participation and the favorableness of the analyst's view of the firm

$$OnCall_{i,j,t} = \beta_0 + \beta_1 Sbuy_{i,j,t} + \beta_2 Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4 Ssell_{i,j,t} + \beta_5 Open_{i,j,t} + \beta_6 NumAnalyst_{i,j,t} + \beta_7 AllStar_{i,j,t} + \beta_8 PriorAcc_{i,j,t} + \beta_9 FirmExp_{i,j,t} + \beta_{10} GenExp_{i,j,t} + \beta_{11} Inds_{i,j,t} + \beta_{12} ForFreq_{i,j,t} + \beta_{13} BrokerSize_{i,j,t} + \beta_{14} Companies_{i,j,t} + \beta_{15} PriorOnCall_{i,j,t} + \beta_{16} RecHorizon_{i,j,t} + \upsilon_{I,j,t} \quad (1)$$

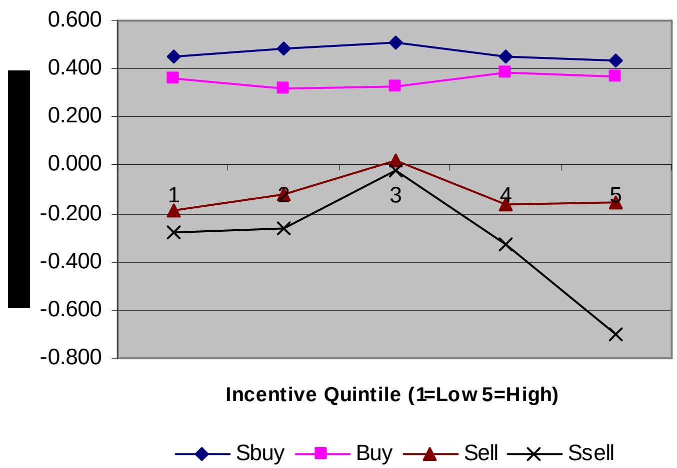
			Column (A) Sample: Unique firm-quarters			***Column (B) Sample: Unique randomly selected analyst-firm-quarter***		
	Variable [a]	**Predicted Sign**	**Coefficients**		**FM t-statistic[c]**	**Coefficients**		**FM t-statistic[c]**
	Intercept	?	-2.552	***	-13.412	-2.603	***	-14.762
Analyst view of the firm								
	Sbuy	+ and > β_2	0.468	***	9.419	0.485	***	14.346
	Buy	+	0.259	***	6.262	0.347	***	12.325
	Sell	-	-0.152	*	-1.364	-0.130	***	-3.694
	Ssell	- and < β_4	-0.309	***	-3.852	-0.356	***	-3.663
Time and Competition Constraints								
	Open	+	2.057	***	10.413	2.092	***	11.148
	NumAnalyst	-	-0.035	***	-9.339	-0.029	***	-11.403
Analyst quality								
	AllStar	+	0.417	***	7.272	0.419	***	24.932
	PriorAcc	+	0.284	***	4.400	0.258	***	6.276
	FirmExp	+	0.040		0.601	0.084	**	2.607
	GenExp	+	0.041		0.672	-0.065		-1.778
	Inds	-	-0.132	***	-3.190	-0.093	***	-4.510
	ForFreq	+	0.142	**	1.999	0.092	*	1.466
	BrokerSize	+	0.054		0.711	0.041		0.851
	Companies	-	0.154	**	3.085	-0.047	**	-1.958
	OnCallPrior	+	1.616	***	12.883	1.580	***	11.213
	RecHorizon	-	-0.001	***	-11.501	-0.001	***	-10.133
	Average Sample Size [b]				2,224			12,226
	Pseudo R^2				14.9%			13.4%

***, **, * significant at .01, .05 and .10 level, respectively, in two-tailed test (one-tailed when predicted).
[a] See Appendix 1 for variable definitions.
[b] The average sample is the average number of observations used in quarterly estimation for the samples identified in Column A and Column B.
[c] Fama MacBeth t-statistic equals the average of 12 quarterly logit coefficient divided by the standard error of these 12 quarterly logit coefficients.

TABLE 8

Effect of Managerial Incentives to Maintain High Stock Prices and Analyst Reliance on Management on Discrimination Extent

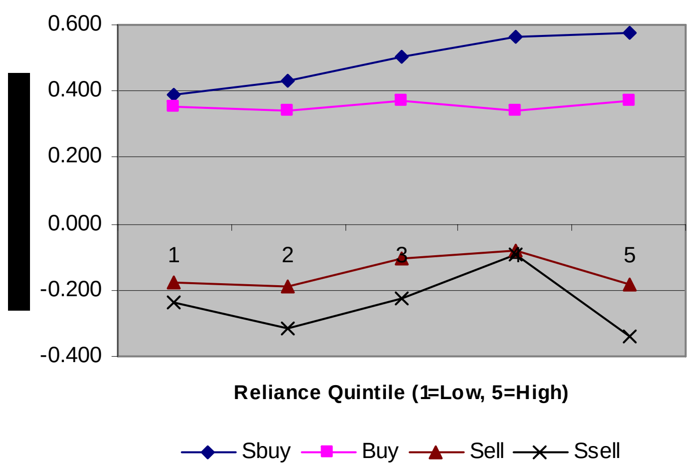
Panel A: Managerial Incentives measured via CEO Option Wealth Sensitivity to Stock Prices



Median CEO Option Wealth Sensitivity ($MM) by Quintile[a]	**Regression Coefficients By Quintile**[b] ***Sbuy***	***Buy***	***Sell***	***Ssell***
Q1 (Low Incentive): 0.03	0.450	0.363	-0.184	-0.275
Q2: 0.13	0.481	0.315	-0.120	-0.260
Q3: 0.28	0.506	0.324	0.018	-0.018
Q4: 0.57	0.455	0.382	-0.161	-0.329
Q5 (High Incentive): 1.69	0.431	0.366	-0.155	-0.698

χ^2 **Test**[c]**:**	**Predicted Sign**	**Coefficient Difference**	**P-Value**	
$Sbuy^{Q5} - Sbuy^{Q1}$	(+)	-0.019	0.830	
$Ssell^{Q5} - Ssell^{Q1}$	(-)	-0.423	0.027	**
$(Sbuy^{Q5} - Ssell^{Q5}) - (Sbuy^{Q1} - Ssell^{Q1})$	(+)	0.405	0.044	**

Panel B: Analyst Reliance on Management measured via Institutional Holdings



Median InstHold By Quintile[a]	**Regression Coefficients By Range**[b] ***Sbuy***	***Buy***	***Sell***	***Ssell***
Q1 (Lowest Reliance): 0.40	0.388	0.355	-0.175	-0.240
Q2: 0.60	0.429	0.342	-0.188	-0.314
Q3: 0.71	0.503	0.373	-0.104	-0.226
Q4: 0.82	0.565	0.344	-0.079	-0.092
Q5 (Highest Reliance): 0.93	0.577	0.370	-0.183	-0.338

χ^2 **Test**[c]**:**	**Predicted Sign**	**Coefficient Difference**	**P-Value**	
$Sbuy^{Q5} - Sbuy^{Q1}$	(+)	0.189	0.003	***
$Ssell^{Q5} - Ssell^{Q1}$	(-)	-0.099	0.291	
$(Sbuy^{Q5} - Ssell^{Q5}) - (Sbuy^{Q1} - Ssell^{Q1})$	(+)	0.288	0.061	*

*, **, *** Significant at the 0.10, 0.05 and 0.01 level (one tailed for signed predictions). Robust standard errors are estimated using the Huber (1967)-White(1980) procedure, with firm level clustering (Rogers 1993)for lack of independence of analyst observations by firm.
[a] See Appendix 1 for variable definitions
[b] Regression coefficients are obtained by running logistic regressions of equation (1) in Table 4 separately over samples pooled by incentive quintiles.

[c] Tests of coefficients between highest and lowest reliance quintiles are obtained by estimating the logistic regression specified as

$OnCall = \sum_{q=Low}^{High}\left(\beta_0^q + \beta_1^q SBuy + \beta_2^q Buy + \beta_3^q Sell + \beta_4^q SSell + \sum_{n=5}^{16}\vec{x}^q\right) + \upsilon$ where q is the incentive quintile of the manager or managerial reliance quintile of the analyst and $\vec{x}$ is the vector of non-stock recommendation level variables in equation (1).

TABLE 9

Ordinary least squares regression investigating the association between the relative queue position of the analyst on the call and the analyst's view of the firm

$$Queue|OnCall_{i,j,t} = \beta_0 + \beta_1\, Sbuy_{i,j,t} + \beta_2\, Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4\, Ssell_{i,j,t} + \beta_5\, AllStar_{i,j,t} + \beta_6\, PriorAcc_{i,j,t} + \beta_7\, FirmExp_{i,j,t} + \beta_8\, GenExp_{i,j,t} + \beta_9\, Inds_{i,j,t} + \beta_{10}\, ForFreq_{i,j,t} + \beta_{11}\, BrokerSize_{i,j,t} + \beta_{12}\, Companies_{i,j,t} + \beta_{13}\, PriorOnCall_{i,j,t} + \upsilon_{I,t} \quad (2)$$

	Variable [a]	Predicted Sign	Coefficients		t-statistics [c]
	Intercept	?	0.373	***	73.56
Analyst view of the firm					
	Sbuy	+ and > β_2	0.044	***	13.81
	Buy	+	0.046	***	15.62
	Sell	-	-0.024	***	-4.43
	Ssell	- and < β_3	-0.017	**	-1.78
Analyst quality					
	AllStar	+	0.049	***	15.49
	PriorAcc	+	0.004		1.03
	FirmExp	+	0.033	***	8.33
	GenExp	+	-0.030	***	-6.80
	Inds	-	-0.003		-0.78
	ForFreq	+	0.006	**	1.67
	BrokerSize	+	0.094	***	23.47
	Companies	-	0.039	***	8.47
	OnCallPrior	+	0.043	***	14.21
	Sample Size [b]		55,489		
	Adjusted R^2		3.7%		

Tests	F-statistic	Prob(F)
$\beta_1 = \beta_2$	0.23	0.633
$\beta_4 = \beta_5$	0.30	0.583

***, **, * significant at .01, .05 and .10 level, respectively, in two-tailed test (one-tailed when predicted).

[a] See Appendix 1 for variable definitions.

[b] The sample includes the subset of 146,708 analyst-firm-quarter observations who participated on the conference call.

[c] t-statistics are calculated using the Newey-West procedure to correct for heteroskedasticity and serial correlation.

TABLE 10

Ordinary least squares regression investigating the association between the time managers spend with the analyst on the conference call and the analyst's view of the firm

$$
\begin{aligned}
Time|OnCall_{i,j,t} = {} & \beta_0 + \beta_1\, SBuy_{i,j,t} + \beta_2\, Buy_{i,j,t} + \beta_3 Sell_{i,j,t} + \beta_4\, SSell_{i,j,t} \\
& + \beta_5\, AllStar_{i,j,t} + \beta_6\, PriorAcc_{i,j,t} + \beta_7\, FirmExp_{i,j,t} \\
& + \beta_8\, GenExp_{i,j,t} + \beta_9\, Inds_{i,j,t} + \beta_{10}\, ForFreq_{i,j,t} + \beta_{11}\, BrokerSize_{i,j,t} \\
& + \beta_{12}\, Companies_{i,j,t} + \beta_{13}\, PriorOnCall_{i,j,t} + \upsilon_{i,t}
\end{aligned} \tag{3}
$$

Variable [a]	Predicted Sign	Coefficients		t-statistics [c]
Intercept	?	2.006	***	56.11
Analyst view of the firm				
Sbuy	+ and > β_2	0.174	***	7.52
Buy	+	0.114	***	5.66
Sell	-	-0.041		-1.20
Ssell	- and < β_3	0.135	*	1.87
Analyst quality				
AllStar	+	-0.093	***	-4.40
PriorAcc	+	-0.181	***	-6.70
FirmExp	+	0.263	***	9.22
GenExp	+	0.055	*	1.65
Inds	-	0.134	***	4.71
ForFreq	+	0.224	***	6.75
BrokerSize	+	0.422	***	13.90
Companies	-	-0.009		-0.21
OnCallPrior	+	0.276	***	13.06
Sample Size [b]		52,060		
Adjusted R^2		1.7%		

Tests	F-statistic	
$\beta_1 = \beta_2$	5.73	***
$\beta_4 = \beta_5$	5.09	**

***, **, * significant at .01, .05 and .10 level, respectively, in two-tailed test (one-tailed when predicted).
[a] See Appendix 1 for variable definitions.
[b] The sample includes the subset of 146,708 analyst-firm-quarter observations who participated on the conference call.
[c] t-statistics are calculated using the Newey-West procedure to correct for heteroskedasticity and serial correlation.

Table 11
Descriptive statistics for 125 randomly selected manager/analyst conference call dialogs

Variable[a]	**Mean**	**Q1**	**Median**	**Q3**	**Std Dev**
Rec	3.000	2.000	3.000	4.000	1.420
SCRUTINIZING	4.576	3.000	4.000	6.000	2.262
OPENENDED	4.512	2.000	4.000	7.000	2.395
TOUGH	4.904	3.000	5.000	7.000	2.198
CHALLENGING	4.960	3.000	5.000	7.000	2.149
NEGNEWS	4.344	3.000	5.000	5.000	1.661
NETPOS_GI	0.029	0.019	0.029	0.039	0.017
Miss	0.288	0.000	0.000	1.000	0.455

[a] See Appendix 2 for variable definitions

Table 12
Correlation Table of Manager/Analyst Dialog Variables (N=125)

	Rec	*SCRUTINIZING*	*OPENENDED*	*TOUGH*	*CHALLENGING*	*NEGNEWS*	*NETPOS_GI*	*Miss*
Rec		-0.226 **	0.119	-0.158 *	-0.151 *	-0.106	0.179 **	-0.162 *
		0.011	0.188	0.079	0.094	0.239	0.046	0.070
SCRUTINIZING	-0.217 **		-0.493 ***	0.754 ***	0.776 ***	0.548 ***	-0.284 ***	0.159 *
	0.015		0.000	0.000	0.000	0.000	0.001	0.077
OPENENDED	0.127	-0.466 ***		-0.567 ***	-0.557 ***	-0.367 ***	0.080	-0.099
	0.158	0.000		0.000	0.000	0.000	0.377	0.270
TOUGH	-0.161 *	0.740 ***	-0.553 ***		0.892 ***	0.508 ***	-0.119	0.084
	0.073	0.000	0.000		0.000	0.000	0.184	0.349
CHALLENGING	-0.153 *	0.773 ***	-0.550 ***	0.891 ***		0.557 ***	-0.224 **	0.152 *
	0.089	0.000	0.000	0.000		0.000	0.012	0.090
NEGNEWS	-0.094	0.545 ***	-0.350 ***	0.496 ***	0.545 ***		-0.129	0.145
	0.296	0.000	0.000	0.000	0.000		0.151	0.106
NETPOS_GI	0.236 ***	-0.250 ***	0.078	-0.148 *	-0.188 **	-0.131		-0.052
	0.008	0.005	0.387	0.099	0.036	0.145		0.563
Miss	-0.162 *	0.157 *	-0.090	0.087	0.159 *	0.129	-0.013	
	0.070	0.080	0.318	0.334	0.077	0.151	0.888	

Notes: ***, **, * indicates the correlation coefficient is significantly different from zero at .01, .05, and .10 levels, respectively. P values are presented below the correlation coefficients. Pearson (Spearman) correlation coefficients are presented above (below) diagonal. See Appendix 2 for variable definitions.

TABLE 13

Ordinary least squares regressions investigating the association between scrutiny proxies and the analyst's view of the firm, partitioned by whether the firm missed earnings targets (n=125).[b]

$$SCRUTINY\_PROXY^{i} = \beta_0^i + \beta_1^i \mathrm{Rec} + \beta_2^i Miss + \beta_3^i (\mathrm{Rec} \times Miss) + \upsilon^i \quad (4)$$

for i = 1 to 6 where i is one of six scrutiny proxies

	Independent Variables[a]								*F statistic*[c]	
***Dependent Variables*[a]**	***Intercept* (β_0)**		***Rec* (β_1)**		***Miss* (β_2)**		***Rec x Miss* (β_3)**		***Test:* $\beta_1 + \beta_3 = 0$**	***Adj R^2***
SCRUTINIZING	5.672	***	-0.488	***	-0.532		0.446	*	0.03	10.16%
Predicted Sign	?		(-)				(+)			
(t-stat)	(10.91)		(-3.28)		(-0.59)		(1.54)			
OPENENDED	3.866	***	0.238	*	-0.154		-0.220		0.00	1.86%
Predicted Sign	?		(+)				(-)			
(t-stat)	(6.55)		(1.39)		(-0.15)		(-0.65)			
TOUGH	6.170	***	-0.487	***	-1.289		0.665	***	0.57	10.20%
Predicted Sign	?		(-)				(+)			
(t-stat)	(12.51)		(-3.42)		(-1.49)		(2.41)			
CHALLENGING	6.239	***	-0.479	***	-0.901		0.581	**	0.21	14.60%
Predicted Sign	?		(-)				(+)			
(t-stat)	(13.02)		(-3.46)		(-1.11)		(2.22)			
NEGNEWS	4.863	***	-0.206	**	-0.495		0.340	*	0.43	3.13%
Predicted Sign	?		(-)				(+)			
(t-stat)	(13.08)		(-1.89)		(-0.71)		(1.47)			
NETPOS_GI	0.018	***	0.003	***	0.011	*	-0.003	**	0.01	7.46%
Predicted Sign	?		(+)				(-)			
(t-stat)	(5.80)		(3.53)		(1.91)		(-1.81)			

***,**, * significant at .01, .05 and .10 level, respectively, in two-tailed test (one tailed when predicted)

[a] See Appendix 2 for variable definitions

[b] The analyses are based on an initial sample of 125 randomly drawn manager/analyst dialogs. Removal of outliers was based on procedures outlined in Besley, et al. (1980) resulted in the following number of observations used in the estimation of each model: SCRUTINIZING (116), OPENENDED (121), TOUGH (113), CHALLENGING (110), NEGNEWS (116), NETPOS_GI (119).

[c] The 0.10 significance critical F-Value is 2.74. In each regression the sum of β_1 and β_3 is not statistically different from zero, suggesting that a relation between *Rec* and each of the scrutiny proxies does not exist when the firm misses earnings targets.

Table 14
Descriptive statistics for 13,188 firm-year observations

Panel A: Distribution of Pooled Sample Variables

Variable[a]	**Mean**	**Q1**	**Median**	**Q3**	**Std Dev**
RECDIFF	0.085	-0.138	0.057	0.296	0.409
NETPOS_GItran	0.032	0.027	0.032	0.037	0.008
DISCRIMINATE	0.546	0.000	1.000	1.000	0.498
CAR	0.002	-0.033	0.004	0.039	0.075
UE	0.000	0.000	0.000	0.001	0.006
BOOKMKT	0.500	0.273	0.438	0.638	0.562
LNMVE	7.540	6.466	7.397	8.527	1.518
RETVOL	0.026	0.016	0.023	0.032	0.013

Panel B: Mean Variable Values by Sign of Earnings Surprise and Conference Call Discrimination

	No News (UE=0)		**Good News Surprise (UE>0)**		**Bad News Surprise (UE<0)**	
Variable[a]	Discriminate = 0	Discriminate = 1	Discriminate = 0	Discriminate = 1	Discriminate = 0	Discriminate = 1
RECDIFF	-0.251	0.374	-0.229	0.343	-0.245	0.367
NETPOS_GItran	0.033	0.033	0.032	0.033	0.030	0.030
CAR	-0.009	-0.016	0.014	0.016	-0.024	-0.021
UE	0.000	0.000	0.003	0.002	-0.004	-0.004
BOOKMKT	0.481	0.447	0.492	0.474	0.555	0.540
LNMVE	6.976	7.226	7.576	7.719	7.261	7.506
RETVOL	0.029	0.027	0.026	0.025	0.028	0.026
N	398	456	3,701	4,685	1,886	2,062
% of Sample	3.0%	3.5%	28.1%	35.5%	14.3%	15.6%

[a] See Appendix 2 for variable definitions

TABLE 15
OLS regressions assessing the earnings response to good and bad news in the presence of discriminating and non-discriminating conference calls

$$CAR_{i,j,t} = \beta_0 + \beta_1 GNNDLarge\_UE_{i,j,t} + \beta_2 GNDCLarge\_UE_{i,j,t} + \beta_3 GNNDSmall\_UE_{i,j,t} + \beta_4 GNDCSmall\_UE_{i,j,t} + \beta_5 BNNDLarge\_UE_{i,j,t} + \beta_6 BNDCLarge\_UE_{i,j,t} + \beta_7 BNNDSmall\_UE_{i,j,t} + \beta_8 GNDCSmall\_UE_{i,j,t} + \beta_9 LNMVE_{i,j,t} + \beta_{10} BOOKMKT_{i,j,t} + \beta_{11} RETVOLi,j,t + \upsilon_{i,j,t} \quad (5)$$

	Robust Pooled Estimation		Fama MacBeth Estimation from 12 quarterly regressions						
Variable[a]	Coefficient Estimate (Newey West t-statistic)[b]		Average Coefficient (Fama MacBeth t-statistic)[d]		# Positive Estimates	# Positive and Significant Estimates	# Negative and Significant Estimates	Z1[d]	Z2[d]
Intercept	0.010	***	0.014	**	8	2	0	3.36	2.25
	(2.49)		(2.21)						
GNNDLarge_UE	1.613	***	2.150	***	10	6	0	7.39	3.73
	(4.45)		(3.46)						
GNDCLarge_UE	2.765	***	3.140	***	11	10	0	13.59	6.74
	(9.47)		(5.71)						
GNNDSmall_UE	8.960	***	9.959	***	12	11	0	11.60	8.46
	(10.29)		(8.17)						
GNDCSmall_UE	9.388	***	10.325	***	12	11	0	15.5	7.23
	(14.25)		(8.77)						
BNNDLarge_UE	1.632	***	2.417	***	12	8	0	8.90	5.85
	(5.70)		(3.70)						
BNDCLarge_UE	2.063	***	2.514	***	12	11	0	11.95	7.22
	(8.79)		(4.68)						
BNNDSmall_UE	9.719	***	9.830	***	12	9	0	8.66	7.58
	(9.04)		(9.58)						
BNDCSmall_UE	7.595	***	7.161	***	12	7	0	8.07	5.60
	(9.04)		(6.52)						
LNMVE	-0.001	**	-0.001		3	1	2	-2.66	-1.97
	(-2.20)		(-1.43)						
BOOKMKT	0.003	**	0.001		8	2	2	0.06	0.04
	(2.23)		(0.44)						
RETVOL	-0.234	***	-0.376	**	3	1	7	-6.26	-2.22
	(-4.03)		(-2.23)						

Table 15 Continued

Adj $R^{2,f}$	7.72%	10.50%
$N^{c,f}$	12,702	1,062

Discrimination Tests:	F Statistic	P Value	Mean Coefficient Difference (discriminate minus non-discriminate)	FM t-statistic[f]	P Value
$\beta_1 = \beta_2$	6.55	0.01	0.990	1.41	0.19
$\beta_3 = \beta_4$	0.20	0.65	0.366	0.29	0.77
$\beta_5 = \beta_6$	1.42	0.23	0.097	0.20	0.85
$\beta_7 = \beta_8$	2.77	0.10	-2.669	-2.44	0.03

[a] See Appendix 2 for variable definitions. ***,**, * significant at .01, .05 and .10 level, respectively, in two-tailed test

[b] t-statistics are calculated using the Newey-West procedure to correct for heteroskedasticity and serial-correlation.

[c] The pooled analyses are based on an initial sample of 13,188 observations. The final sample used in estimation removes outliers based on procedures outlined in Besley, et al. (1980). Earnings partitions represent the following number of observations (% of 13,188 observations): *BNNDSmall_UE* 1,227 (9%), *BNNDLarge_UE* 300 (2%), *BNDCSmall_UE* 1,983 (15%), *BNDCLarge_UE* 438 (3%), *GNNDSmall_UE* 2,994 (23%), *GNNDLarge_UE* 357 (3%), *GNDCSmall_UE* 5,249 (40%), and *GNDCLarge_UE* 640 (5%).

[d] Fama MacBeth t-statistic is calculated as the mean coefficient across 12 regressions divided by the standard error of the coefficients. Z1 and Z2 test whether the time-series mean t-statistic equals zero. Z1 = $(1/\sqrt{N})\sum_{j=1}^{12} t_j / \sqrt{k_j/(k_{j-2})}$ where t_j is the t-statistic for quarter j, k_j is the degrees of freedom for quarter j, and N is the number of quarters. Z2 = $\bar{t}/(stddev(t)/\sqrt{N-1}$. Critical values for |Z1| and |Z2| are 1.782, 2.681 and 3.106 for significance at the two-tailed 10%, 5% and 1% levels. See Barth (1994) for discussion and use of Z1 and Z2 and application in Barth (1994) and Aboody and Lev (1998).

[c] Fama MacBeth t-statistics for differences across coefficients are calculated as the mean difference in coefficients across the 12 regressions divided by the standard error of the coefficients.

[f] Fama MacBeth adjusted r-square values (sample sizes) are the average r-square values (sample sizes) from 12 quarterly regressions.

TABLE 16

Ordinary least squares regressions assessing the earnings response to good and bad news in the presence of discriminating and non-discriminating conference calls using alternative definitions of abnormal announcement period returns

$$DV_{i,j,t} = \beta_0 + \beta_1\, GNNDLarge\_UE_{i,j,t} + \beta_2\, GNDCLarge\_UE_{i,j,t} + \beta_3 GNNDSmall\_UE_{i,j,t} + \beta_4\, GNDCSmall\_UE_{i,j,t} + \beta_5\, BNNDLarge\_UE_{i,j,t} + \beta_6\, BNDCLarge\_UE_{i,j,t} + \beta_7\, BNNDSmall\_UE_{i,j,t} + \beta_8\, BNDCSmall\_UE_{i,j,t} + \beta_9\, LNMVE_{i,j,t} + \beta_{10}\, BOOKMKT_{i,j,t} + \beta_{11}\, RETVOLi,j,t + \upsilon_{i,j,t} \quad \textbf{(5)}$$

	DV = Equal Weighted CRSP adjusted CAR		DV = size adjusted CAR	
Variable[a]	**Coefficient Estimate (Newey West t-statistic)[b]**		**Coefficient Estimate (Newey West t-statistic)[b]**	
Intercept	0.017	***	0.012	***
	(4.06)		(2.83)	
GNNDLarge_UE	1.854	***	1.759	***
	(5.09)		(4.94)	
GNDCLarge_UE	2.876	***	2.751	***
	(9.97)		(9.48)	
GNNDSmall_UE	9.128	***	9.177	***
	(10.51)		(10.54)	
GNDCSmall_UE	10.041	***	9.622	***
	(15.25)		(14.56)	
BNNDLarge_UE	1.468	***	1.530	***
	(5.18)		(5.48)	
BNDCLarge_UE	2.041	***	2.031	***
	(8.57)		(8.59)	
BNNDSmall_UE	8.885	***	9.446	***
	(8.48)		(8.96)	
BNDCSmall_UE	7.124	***	7.661	***
	(8.32)		(9.00)	
LNMVE	-0.001	***	-0.001	***
	(-3.53)		(-2.55)	
BOOKMKT	-0.000		0.003	
	(-0.09)		(1.65)	

Table 16 Continued

RETVOL	-0.340 ***		-0.239 ***	
	(-5.84)		(-4.09)	
Adj R^2	7.81%		7.68%	
N[c]	12,712		12,587	
Discrimination Tests:	**F Statistic**	**P Value**	**F Statistic**	**P Value**
$\beta_1 = \beta_2$	5.18	0.02	5.01	0.03
$\beta_3 = \beta_4$	0.92	0.34	0.22	0.64
$\beta_5 = \beta_6$	2.50	0.11	1.97	0.16
$\beta_7 = \beta_8$	1.94	0.16	1.99	0.16

Notes to Table 16
***,**, * significant at .01, .05 and .10 level, respectively, in two-tailed test
[a] See Appendix 2 for variable definitions.
[b] t-statistics are calculated using the Newey-West procedure to correct for heteroskedasticity and serial-correlation.
[c] The analyses are based on an initial sample of 13,188 observations. The final sample used in estimation removes outliers based on procedures outlined in Besley, et al. (1980).

TABLE 17
OLS regressions assessing the earnings response to good and bad news during discriminating and non-discriminating conference calls partitioned by investor sophistication

$$\begin{aligned} CAR_{i,j,t} = \; & HighSoph \times (\beta_0 + \beta_1 GNNDLarge\_UE_{i,j,t} + \beta_2 GNDCLarge\_UE_{i,j,t} + \beta_3 GNNDSmall\_UE_{i,j,t} \\ & + \beta_4 GNDCSmall\_UE_{i,j,t} + \beta_5 BNNDLarge\_UE_{i,j,t} + \beta_6 BNDCLarge\_UE_{i,j,t} \\ & + \beta_7 BNNDSmall\_UE_{i,j,t} + \beta_8 BNDCSmall\_UE_{i,j,t} + \beta_9 LNMVE_{i,j,t} \\ & + \beta_{10} BOOKMKT_{i,j,t} + \beta_{11} RETVOL_{i,j,t}) + \\ & LowSoph \times (\alpha_0 + \alpha_1 GNNDLarge\_UE_{i,j,t} + \alpha_2 GNDCLarge\_UE_{i,j,t} + \alpha_3 GNNDSmall\_UE_{i,j,t} \\ & + \alpha_4 GNDCSmall\_UE_{i,j,t} + \alpha_5 BNNDLarge\_UE_{i,j,t} + \alpha_6 BNDCLarge\_UE_{i,j,t} \\ & + \alpha_7 BNNDSmall\_UE_{i,j,t} + \alpha_8 BNDCSmall\_UE_{i,j,t} + \alpha_9 LNMVE_{i,j,t} \\ & + \alpha_{10} BOOKMKT_{i,j,t} + \alpha_{11} RETVOL_{i,j,t}) + \upsilon_{i,j,t} \end{aligned} \quad (6)$$

	(sophistication proxy = institutional holdings)[d]				(sophistication proxy = analyst following)[d]			
	Low Investor Sophistication		High Investor Sophistication		Low Investor Sophistication		High Investor Sophistication	
Variable[a]	**Coefficient Estimate (Newey West t-statistic)[b]**		**Coefficient Estimate (Newey West t-statistic)[b]**		**Coefficient Estimate (Newey West t-statistic)[b]**		**Coefficient Estimate (Newey West t-statistic)[b]**	
Intercept	0.026	***	-0.029	***	0.016	**	0.000	
	(3.99)		(-2.72)		(1.82)		(0.04)	
GNNDLarge_UE	1.542	***	1.064	*	1.392	***	0.400	
	(2.83)		(1.71)		(2.55)		(0.49)	
GNDCLarge_UE	2.912	***	3.300	***	2.976	***	3.241	***
	(6.73)		(5.57)		(6.73)		(4.25)	
GNNDSmall_UE	8.288	***	9.513	***	6.302	***	8.965	***
	(5.99)		(5.86)		(4.30)		(5.59)	
GNDCSmall_UE	8.691	***	11.754	***	7.786	***	10.713	***
	(7.78)		(9.77)		(7.26)		(8.30)	
BNNDLarge_UE	1.807	***	-0.007		1.439	***	0.675	
	(4.08)		(-0.01)		(3.21)		(0.76)	
BNDCLarge_UE	1.916	***	1.732	***	1.753	***	2.595	***
	(5.47)		(3.85)		(5.61)		(3.79)	
BNNDSmall_UE	9.436	***	9.194	***	11.627	***	11.623	***
	(5.47)		(4.74)		(6.34)		(5.45)	
BNDCSmall_UE	7.499	***	7.257	***	7.332	***	8.511	***
	(6.13)		(4.52)		(5.54)		(4.86)	

Table 17 Continued

LNMVE	-0.002	***	0.000		-0.002		-0.001	*
	(-3.56)		(0.17)		(-1.53)		(-1.86)	
BOOKMKT	-0.001		0.000		0.004		-0.005	*
	(-0.32)		(0.14)		(1.55)		(-1.65)	
RETVOL	-0.490	***	0.137		-0.294	*	-0.102	
	(-5.16)		(1.21)		(-2.89)		(-0.90)	
Adj R^2	8.42%				7.39%			
N[c]	8,486				7,812			

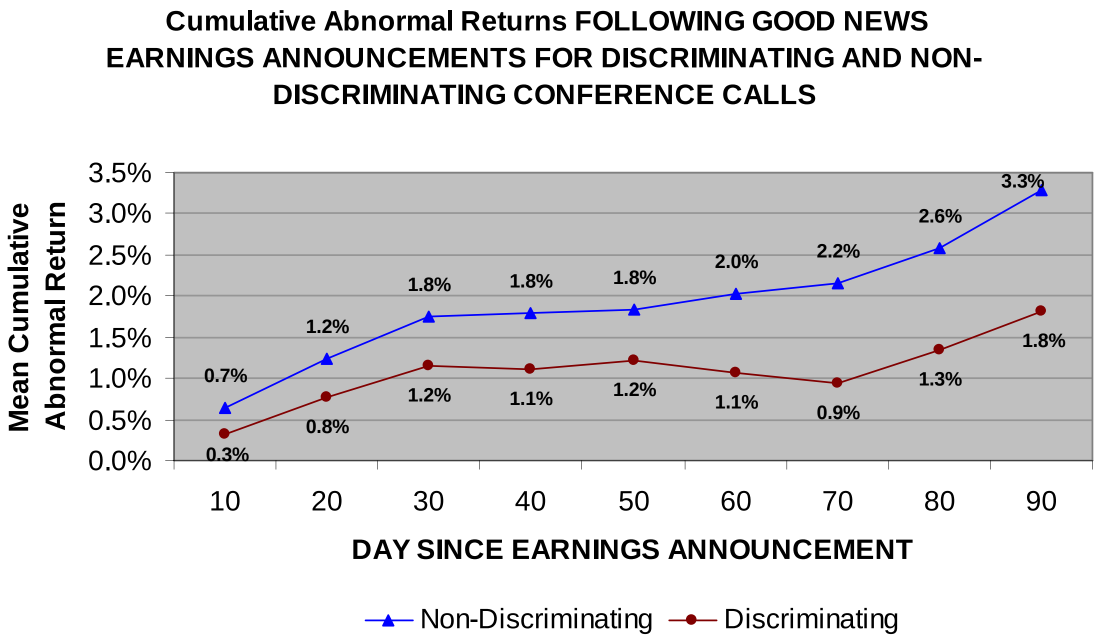
Discrimination Tests:	**F Statistic**	**P Value**	**F Statistic**	**P Value**
$\beta_1 = \beta_2$	7.08	0.01	6.43	0.01
$\beta_3 = \beta_4$	1.61	0.20	0.94	0.33
$\beta_5 = \beta_6$	6.32	0.01	2.80	0.09
$\beta_7 = \beta_8$	0.66	0.42	1.45	0.23
$\alpha_1 = \alpha_2$	4.24	0.04	5.57	0.02
$\alpha_3 = \alpha_4$	0.07	0.80	0.88	0.35
$\alpha_5 = \alpha_6$	0.04	0.84	0.35	0.55
$\alpha_7 = \alpha_8$	0.99	0.32	4.26	0.04

Notes to Table 17:
***,**, * significant at .01, .05 and .10 level, respectively, in two-tailed test

[a] See Appendix 2 for variable definitions.

[b] t-statistics are calculated using the Newey-West procedure to correct for heteroskedasticity and serial-correlation.
[c] The analyses are based on a sample of 8,486 (7,812) observations for the institutional holdings (analyst following) partitions. This sample results from removing the middle 1/3 of observations on the institutional holdings (analyst following) variable, where such a measure was available, from the original initial sample of 13,188. The final sample used in estimation removes outliers based on procedures outlined in Besley, et al. (1980).
[d] I proxy for investor sophistication in two ways, consistent with Schrand and Walther (2000). The first method uses the extent of institutional holdings as of the most recent calendar quarter proceeding the fiscal quarter end. High (low) sophistication, *HighSoph* (*LowSoph*) equals 1 if the firm-quarter observation falls in the top (bottom) third of the pooled distribution of institutional holdings. The middle third observations are removed from the sample. The second method uses the number of analysts contributing to the quarterly earnings forecast per I/B/E/S. High (low) sophistication, *HighSoph* (*LowSoph*) equals 1 if the firm-quarter observation falls in the top (bottom) third of the pooled distribution of analyst following. The middle third observations are removed from the sample.

Table 18: Plots of Good News Earnings Announcement CARs



Notes to Table 18: Mean cumulative abnormal return differences between discriminating and non-discriminating firms are statistically different from zero at better than the 5% level (two-tailed) at each day increment displayed, except 50 days since the earnings announcement, which is significant at better than the 10% level (two tailed).

Sample Construction: Sample contains the set of 8,386 good news earnings announcement firms (i.e. UE>0), of which 4,685 held discriminating conference calls and 3,701 held non-discriminating conference calls.

Variable Definitions:

Cumulative Abnormal Return (CARs) = daily raw return for each stock minus the CRSP value weighted index daily return, cumulated over the period (+2,+n), where n is the number of days since the earnings announcement and equals the following values in the set (10, 20, 30, 40, 50, 60, 70, 80, 90).

Non-Discriminating: Portfolio of stocks where Recdiff <=0.

Discriminating: Portfolio of good news earnings announcements where Recdiff > 0.

APPENDIX 1: VARIABLE DEFINITIONS – Chapter 2

Firm Level Variables	
Assets - Total ($MM)	Total assets at fiscal quarter end (data14 from CRSP/Compustat quarterly merged database)
Market Value of Equity ($MM)	Market value of equity at fiscal quarter end (data14*data61 from CRSP/Compustat quarterly merged database)
Market to Book Ratio	Market value of equity to book value of equity at fiscal quarter end (data14*data61/data60 from CRSP/Compustat quarterly merged database)
Return on Assets	Return on Assets at fiscal quarter end (data25/data44 from CRSP/Compustat quarterly merged database)
CorpCount	Total number of corporate participants on the call per the transcript
NonCorpCount	Total number of non-corporate participants on the call per the transcript
NumAnalyst	Number of sample analysts providing earnings forecasts and recommendations on I/B/E/S for the current fiscal quarter end
IBESonCall	Number of I/B/E/S analysts providing earnings estimates and recommendations for the current fiscal quarter that participate on the conference call
IBESonCallDum	Equals 1 if there is at least one IBES analyst covering the firm at quarter end who participates on the conference call, 0 otherwise
Length of Conference Call (min)	Length of conference call in minutes (where minutes is derived from total word count of transcript at 150 words per minute)
Length of Q&A (min)	Length of question and answer portion of the call, in minutes
Open	Openness of the conference call measured as the ratio of time spent on the question and answer portion of the call divided by the total time of the conference call
MarketEst	The consensus mean earnings per share calculated using all sample analysts who provided earnings estimates for the current fiscal quarter end
OnCallEst	Mean earnings estimate of the sample analysts who participated on the conference call
Actual	Actual reported earnings per share per I/B/E/S
MarketFE	The raw forecast error for all sample analysts covering the firm on I/B/E/S (Actual - MarketEst)
OnCallFE	The raw forecast error for those sample analysts participating on the conference call (Actual - OnCallEst)
MarketRec	The consensus mean stock recommendation using all sample analysts who provided earnings estimates for the current fiscal quarter end
OnCallRec	Mean stock recommendation of the sample analysts who participated on the conference call
CEO option wealth sensitivity ($MM)	Change in CEO wealth from option holdings, in Millions, to a 1 percent change in stock price, calculated as the derivative of total option holdings at most recent fiscal year end with respect to price (Core and Guay, 2002). Total option holdings are calculated as the sum of exercisable and unexercisable options outstanding per Execucomp at most recent fiscal year end. Option inputs to calculate Black Scholes option values are as follows: Time to maturity is assumed to be 7.5 years. Volatility is measured over the period from the midpoint of the most recent fiscal year end through 5 years prior to that date. Dividend yield is the average dividend yield over the most recent 3 years. Strike and exercise prices equal the exercise price of current year option grants.
InstHold	Percentage of institutional holdings as of the most recent calendar quarter prior to the current fiscal quarter end per 13(f) filing

Appendix 1: Variable Definitions (continued)

Analyst Level Variables	
OnCall	Analyst participation on the conference call measured as 1 if the analyst asked a question during the conference call and 0 otherwise
IBESRec	Analyst stock recommendation as originally coded in I/B/E/S immediately prior to the conference call date. I/B/E/S codes strong buy as 1, buy as 2, hold as 3, sell as 4 and strong sell as 5.
Sbuy	Strong buy recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a strong buy, 0 otherwise
Buy	Buy recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a buy, 0 otherwise
Hold	Hold recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a hold, 0 otherwise
Sell	Sell recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a sell, 0 otherwise
Ssell	Strong sell recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a strong sell, 0 otherwise
RelRec	Relative stock recommendation, where values of 1 on this variable mean the analyst is the most favorable relative to other analysts following the firm, and 0 indicates the analyst is the least favorable relative to other analysts following the firm. *RelRec* calculated as the outstanding stock recommendation of analyst i following firm j in quarter t minus the smallest recommendation by any analyst following firm j in quarter t, with this difference scaled by the range in the recommendation any analyst following firm j in quarter t. Recommendations are obtained from I/B/E/S and are recoded so that strong buy =5, buy = 4, hold = 3, sell = 2 and strong sell = 1.
RecChange	The difference between the stock recommendation of analyst i following firm j in quarter t minus the stock recommendation of analyst i following firm j in quarter t-1, where stock recommendations are obtained from I/B/E/S and are recoded so that strong buy =5, buy = 4, hold = 3, sell = 2 and strong sell = 1. Thus, positive values on *RecChange* indicate an analyst upgraded the stock and negative values indicate downgrades.
AllStar	All Star research analyst measured as 1 if the analyst made any of the Institutional Investor Research All-American teams as of the most recent prior year, 0 otherwise
PriorAcc	Prior earnings forecast accuracy, measured as the relative absolute forecast error of the analyst's prior quarter earnings forecast. Relative absolute forecast error is calculated as the prior quarter absolute forecast error for analyst i following firm j in quarter t minus the smallest forecast error by any analyst following firm j in quarter t, with this difference scaled by the range in the prior quarter absolute forecast error for all analysts following firm j in quarter t.
FirmExp_Raw	Number of years the analyst has been following the firm, measured as the difference between the conference call date and the date of the analyst's first earnings estimate for the firm on I/B/E/S, scaled by 365
FirmExp	Firm experience measured as the relative time the analyst has covered the firm, where firm coverage is measured as the number of days between the conference call date and the analyst's first earnings forecast estimate date on I/B/E/S for the firm. Relative firm experience is calculated as the firm experience for analyst i following firm j in quarter t minus the smallest firm experience by any analyst following firm j in quarter t, with this difference scaled by the range in the firm experience for all analysts following firm j in quarter t.
GenExp_Raw	Number of years the analyst has been on I/B/E/S measured as the difference between the conference call date and the date of the analyst's first earnings estimate on I/B/E/S, scaled by 365

Appendix 1: Variable Definitions (continued)

GenExp	General experience measured as the relative time the analyst has been on I/B/E/S where time on I/B/E/S is measured as the number of days between the conference call date and the analyst's first earnings forecast estimate date on I/B/E/S for any firm. Relative general experience is calculated as the general experience for analyst i following firm j in quarter t minus the smallest general experience by any analyst following firm j in quarter t, with this difference scaled by the range in the general experience for all analysts following firm j in quarter t.
Inds_Raw	Then number of two digit SIC code industries followed by the analyst during the most recently completed calendar year prior to the conference call date
Inds	Industry coverage measured as the relative number of industries covered by the analyst over the most recently completed calendar year prior to the conference call date. Relative industry coverage is calculated as the industry coverage of analyst i following firm j in quarter t minus the smallest industry coverage by any analyst following firm j in quarter t, with this difference scaled by the range in industry coverage for all analysts following firm j in quarter t.
ForFreq_Raw	Then number of quarterly earnings forecasts made for the firm during the most recently completed calendar year
ForFreq	Forecast frequency measured as the relative number of quarterly earnings forecasts issued by the analyst for the firm over the most recently completed calendar year prior to the conference call date. Relative forecast frequency is calculated as the forecast frequency for analyst i following firm j in quarter t minus the lowest forecast frequency by any analyst following firm j in quarter t, with this difference scaled by the range in the forecast frequency for all analysts following firm j in quarter t.
BrokerSize_Raw	The number of analysts employed by the brokerage house employing the analyst as of the most recently completed calendar year prior to the conference call date
BrokerSize	Broker size measured as the relative number of analysts employed by the brokerage firm employing the analyst during the most recent calendar year prior to the conference call date. Relative broker size is calculated as the broker size for analyst i following firm j in quarter t minus the smallest broker size of any analyst following firm j in quarter t, with this difference scaled by the range in broker size for all analysts following firm j in quarter t.
Companies_Raw	Number of companies covered by the analyst during the most recently completed calendar year prior to the conference call date
Companies	Company coverage measured as the relative number of companies followed by the analyst over the most recently completed calendar year prior to the conference call date. Relative company coverage is calculated as the company coverage of analyst i following firm j in quarter t minus the lowest company coverage by any analyst following firm j in quarter t, with this difference scaled by the range in company coverage for all analysts following firm j in quarter t.
OnCallPrior	Prior conference call participation measured as 1 if the analyst was identified as asking a question on any of the firm's prior conference calls in the sample, and 0 otherwise.
RecHorizon	Forecast horizon measured as the number of days between the conference call date and the date of the analysts most recent stock recommendation
Queue|OnCall	The order of the analyst's first appearance on the conference call relative to all non-corporate conference call participants. Relative order is calculated as (Total number of non-corporate conference call participants - position of analyst on conference call)/(Total number of non-corporate conference call participants - 1). The last non-corporate participant to ask a question has a value of 0, while the first non-corporate participant to ask a question has a value of 1.
Time|OnCall	The number of minutes managers spend answering questions of the analyst, measured as the number of words spoken to the analyst divided by 150, where 150 is the word count per minute conversion

APPENDIX 2: VARIABLE DEFINITIONS – Chapter 3

Rec	Individual analyst outstanding stock recommendation immediately prior to the earnings conference call per I/B/E/S/. Recommendation values have been coded to reverse the order in I/B/E/S such that more favorable recommendations have higher values (1 for Strong Sell, 2 for Sell, 3 for Hold, 4 for Buy and 5 for Strong Buy)
SCRUTINIZING	Likert scale response to the following question on a scale of 1 (Not Scrutinizing at all) to 9 (Very Scrutinizing): Overall, on the following scale from 1 to 9, how scrutinizing do you feel the analyst's question(s) of management were?
OPENENDED	Likert scale response to the following question on a scale of 1 (Direct) to 9 (Open ended): Overall, on the following scale from 1 to 9, would you characterize the analyst's question(s) of management to be direct or open ended?
TOUGH	Likert scale response to the following question on a scale of 1 (Softball) to 9 (Tough): Overall, on the following scale from 1 to 9, did the analyst ask 'softball' questions or 'tough' questions?
CHALLENGING	Likert scale response to the following question on a scale of 1 (Catered) to 9 (Challenged): Overall, on a scale from 1 to 9, did the analyst ask questions that catered to or challenged the manager?
NEGNEWS	Likert scale response to the following question on a scale of 1 (Positive news) to 9 (Negative news): Overall, on a scale from 1 to 9, would you characterize the information ultimately provided by the manager as a result of the dialog with the analyst as positive or negative news about the firm?
NETPOS_GI	The difference between the number of positive words as identified by the General Inquirer software and the number of negative words identified by the General Inquirer software, scaled by the total number of words identified in the manager-analyst dialog.
Miss	Dummy variable that equals 1 if the firm's actual earnings per share as reported in I/B/E/S was less than the mean earnings forecast calculated from all I/B/E/S analysts issuing earnings forecasts 60 days prior to the conference call, and zero otherwise. When an analyst issues more than one forecast during this period, the most recent forecast is used for calculating the consensus.
Discriminate	Indicator variable that equals one if RecDiff >= 0, zero otherwise.
RecDiff	Difference between the average outstanding recommendations of all analysts that participated on the conference call by asking a question minus the average of outstanding recommendations for all analysts following the firm. Positive values on this variable indicate that the analysts participating on the conference call had more optimistic views of the firm than the underlying population of analysts. Individual analyst stock recommendations are coded as 5 for strong buy, 4 for buy, 3 for hold, 2 for sell, and 1 for strong sell.
MarketRec	The consensus mean stock recommendation using all sample analysts who provided earnings estimates for the current fiscal quarter end per I/B/E/S.
NETPOS_GItran	The difference between the number of positive words as identified by the General Inquirer software and the number of negative words identified by the General Inquirer software, scaled by the total number of words identified in the entire question and answer session of the conference call.

Appendix 2: Variable Definitions (continued)

UE	Unexpected quarterly earnings per share scaled by the market value of equity per share 2 days prior to the earnings announcement. Unexpected quarterly earnings per share is measured as the difference between actual reported quarterly earnings per share in I/B/E/S and the mean earnings forecast calculated from all I/B/E/S analysts issuing earnings forecasts 60 days prior to the conference call. When an analyst issues more than one forecast during this period, the most recent earnings forecast is used for calculating expected earnings.
CAR	Cumulative Abnormal Returns, calculated as the firm's daily raw returns minus value weighted CRSP market returns, cumulated over the three days centered on the conference call date.
RETVOL	Equals the standard deviation of daily stock return volatilities calculated over the 100 trading days ending two days prior to the conference call date.
LNMVE	Natural logarithm of market value of equity at fiscal quarter end (data14*data61 from CRSP/Compustat quarterly merged database)
Large_UE	Indicator variable that equals UE if |UE| > .005, and zero otherwise. Freeman and Tse (1992) document that that the linear returns earnings relation is well specified when the earnings surprise is no greater than .5% of firm value.
GN	Good news earnings: Indicator variable that equals 1 if the firm met or beat earnings expectations (i.e. UE >= 0), zero otherwise.
BN	Bad news earnings: Indicator variable that equals 1 if the firm missed earnings expectations (i.e. UE < 0), zero otherwise.
GNNDLarge_UE	Equals UE when GN =1, Discriminate = 0, and Large_UE = 1, and zero otherwise
GNDCLarge_UE	Equals UE when GN =1, Discriminate = 1, and Large_UE = 1, and zero otherwise
GNNDSmall_UE	Equals UE when GN =1, Discriminate = 0, and Large_UE = 0, and zero otherwise
GNDCSmall_UE	Equals UE when GN =1, Discriminate = 1, and Large_UE = 0, and zero otherwise
BNNDLarge_UE	Equals UE when GN =0, Discriminate = 0, and Large_UE = 1, and zero otherwise
BNDCLarge_UE	Equals UE when GN =0, Discriminate = 1, and Large_UE = 1, and zero otherwise
BNNDSmall_UE	Equals UE when GN =0, Discriminate = 0, and Large_UE = 0, and zero otherwise
BNDCSmall_UE	Equals UE when GN =0, Discriminate = 1, and Large_UE = 0, and zero otherwise
BOOKMKT	Book value of common equity divided by market value of common equity as of fiscal quarter end.

Appendix 3 – Discussion of Linguistic Software Package

General Inquirer

The General Inquirer (GI) is a content analysis software package developed and written by Philip Stone and collegues at Harvard University (http://www.wjh.harvard.edu/~inquirer/). The GI identifies and counts word frequencies and word senses in submitted text files and matches them against words present in the "Harvard IV-4" dictionary. This dictionary has numerous categories into which it can classify words. The two categories used for this study are Positive and Negative, consistent with Kothari and Short (2003). Positive is a category that includes 1,915 words of positive outlook. Negative is a category that includes 2,291 words of negative outlook. For each text file submitted to GI, an output report is provided that counts the total number of words in the text file as well as the number of words that fall into each of the dictionary categories. In the context of this study, conference call transcripts were used as text file inputs. Interpreting GI output is ultimately an issue of comparing word counts and frequencies across dictionary categories. Text analysis software has no ability to ascertain contextual meaning that results from the combination of consecutive words in a text document. In this research, the difference between the number of positive and negative words is used as a proxy for the positivity of a conference call dialog.

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